TRAFFIC INPUTS FOR PAVEMENT ME DESIGN

USING OKLAHOMA DATA

By

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Abstract: Mechanistic-empirical pavement design guide (MEPDG) requires traffic inputs in three levels based on the availability of data and scale of the project.
Site-specific (Level 1) data is high quality and can be obtained by automated traffic data collection techniques like Automatic Vehicle Classification (AVC) and Weigh-in-motion (WIM) data. However, available of Level 1 data is limited and even it is very expensive to obtain data. On the other side, statewide default (Level 3) data has the lowest quality. So, regional-specific (Level 2) with medium quality need to be developed. However, automatic data have errors; this happens more with WIM data. To ensure the quality of data, this research is started with developing QC metrics for the Oklahoma state WIM data and then generating site-specific (Level 1), region-specific (Level 2), and statewide average (Level 3) traffic inputs that are required for the Pavement ME Design in Oklahoma. This process includes performing a comprehensive check for the quality of data by using a software Prep-ME followed by manual review. Developed and presented homogeneous groups for each traffic input by analyzing data with K-means cluster analysis techniques for regional specific (Level 2) inputs. Investigated and identified the available independent variables that are influencing the traffic cluster groups. Decision tree model and Multinomial regression model are developed by training them with available data from multiple stations and multiple years. These models can identify the suitable cluster group for the given site conditions. To evaluate the variation in pavement performance for Level 2 and Level 3 traffic inputs, case study is included. This study can provide a set of procedures and methodology to assist design engineers in developing regional-specific (Level 2) traffic inputs for pavement ME Design in the Oklahoma.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Figure **Page**

CHAPTER I

1 INTRODUCTION

1.1 Background

Traffic loads are one of the key data elements required for the design and analysis of pavement structures. Traditionally the mixed traffic stream was aggregated into equivalent single-axle loads (ESALs). The Mechanistic-Empirical Pavement Design Guide (MEPDG), later named as DARWin-ME and Pavement ME Design, proposes a more rational approach to characterize traffic regarding full axle-load spectrum. It provides users with the flexibility to input three levels of traffic inputs based on data availability and the importance of the project: Level 1 site-specific with the highest quality, Level 2 regional specific with medium quality, and Level 3 state or national defaults with the lowest quality. To meet the traffic data requirements in DARWin-ME, automated traffic collection techniques are needed. However, automated traffic data often have errors, particularly for data collected from weigh-in-motion (WIM) sites. A national study concludes that only 15% to 25% of the WIM data collected are of "good" quality (Lu and Harvey, 2006). One of the primary causes is that many state agencies are lacking in staffing, resources, and relevant supporting software to examine the huge amount of raw WIM data for quality assurance (QA), while most WIM sensor vendors do not include details for quality control (QC) in reports. It is impractical to manually process the data files even with computer assistance, and this process needs to be automated with software for routine implementation.

Also, with a limited number of available WIM sites within a state highway agency, how to generate traffic inputs required in MEPDG for any design location remains a challenge. If no prior Level 1 traffic WIM data are available for a pavement design, utilizing Level 3 state-wide default traffic input parameters may lead to the estimation of inconsistent pavement performance. Therefore, Level 2 regional traffic inputs should be developed and used for pavement design by combining existing site-specific data from WIM systems located on sites that exhibit similar traffic characteristics. How to qualify these similarities and develop loading groups (also called traffic clusters) are therefore critical for the successful implementation of Pavement ME Design at any design location.

Currently, Oklahoma Department of Transportation (ODOT) operates approximately 90 Automatic vehicle classification stations, out of which 20 are WIM stations. It is vital to utilize the abundant WIM data sets and develop such traffic input parameters for ODOT to successfully implement the DARWin-ME. Recognizing that no comprehensive study has been conducted to evaluate the statewide WIM data quality, in this study we propose to develop WIM quality control metrics and associated software interfaces for checking the quality of Oklahoma WIM data and generating site-specific (Level 1), region-specific (Level 2), and statewide (Level 3) traffic inputs that are required for local calibration and implementation of the Pavement ME Design in Oklahoma.

1.2 Objectives

The objective of this research is to develop WIM QC metrics and generate site-specific (Level 1), region-specific (Level 2), and statewide average (Level 3) traffic inputs that are required for the Pavement ME Design in Oklahoma. This research will include the following tasks to achieve the objective: (1) perform a comprehensive review of current literature and methodologies on AVC and WIM data quality, use of this data for DARWin-ME and independent variables influencing the traffic patterns; (2) conduct automatic statewide AVC and WIM data check using Prep-ME software followed by manual QC to evaluate the accuracy of sensor data; (3) develop site specific (Level 1) traffic inputs at each WIM location, perform cluster analysis to develop region-specific (Level 2) traffic clusters and loading groups, statewide average (Level 3) traffic inputs for any design location in Oklahoma; (4) identifying the independent variables that are influencing the clusters and perform sensitivity analysis; (5) developing decision trees, discriminate regression models for selecting clusters for regional-specific (Level 2) traffic inputs; (6) finally evaluate the accuracy of pavement performance prediction by ME-PDG for level-2 and level 3 traffic inputs.

1.3 Report Outline

This thesis is organized into six chapters, as shown in Figure 1.1. Chapter 1 provides the background and the presents the objectives and tasks of this project.

In Chapter 2, a summary of a comprehensive literature review is provided aiming to develop an in-depth understanding of traffic input parameters and sensitivity analysis of those traffic inputs for MEPDG. In particular traffic data input requirements and existing research efforts, WIM systems data quality check methods, how WIM data are used to generate axle loading spectra and volume adjustment factors for MEPDG, and related sensitivity analyses are investigated.

Chapter 3 primarily focuses on the importing the raw WIM data and VCD data using the Prep-ME software, and discusses the methodology adopted to ensure the quality of data also to enhance the data quality. Latter part of the chapter explains the traffic characteristics and inputs for MEPGD.

In chapter 4, the methodology followed to develop the clusters for level 2 traffic inputs.

Chapter 5 discusses the techniques to identify the independent variables and selection of clusters based on the independent variables. Both decision trees and discriminant regression based models are investigated.

Chapters 6 evaluate the accuracy of pavement performance prediction by ME-PDG and required flexible pavement structure according to AASHTO 1993 guide for level-2 and level 3 traffic inputs.

Chapter 7 summarizes the whole study and presents the recommendations.

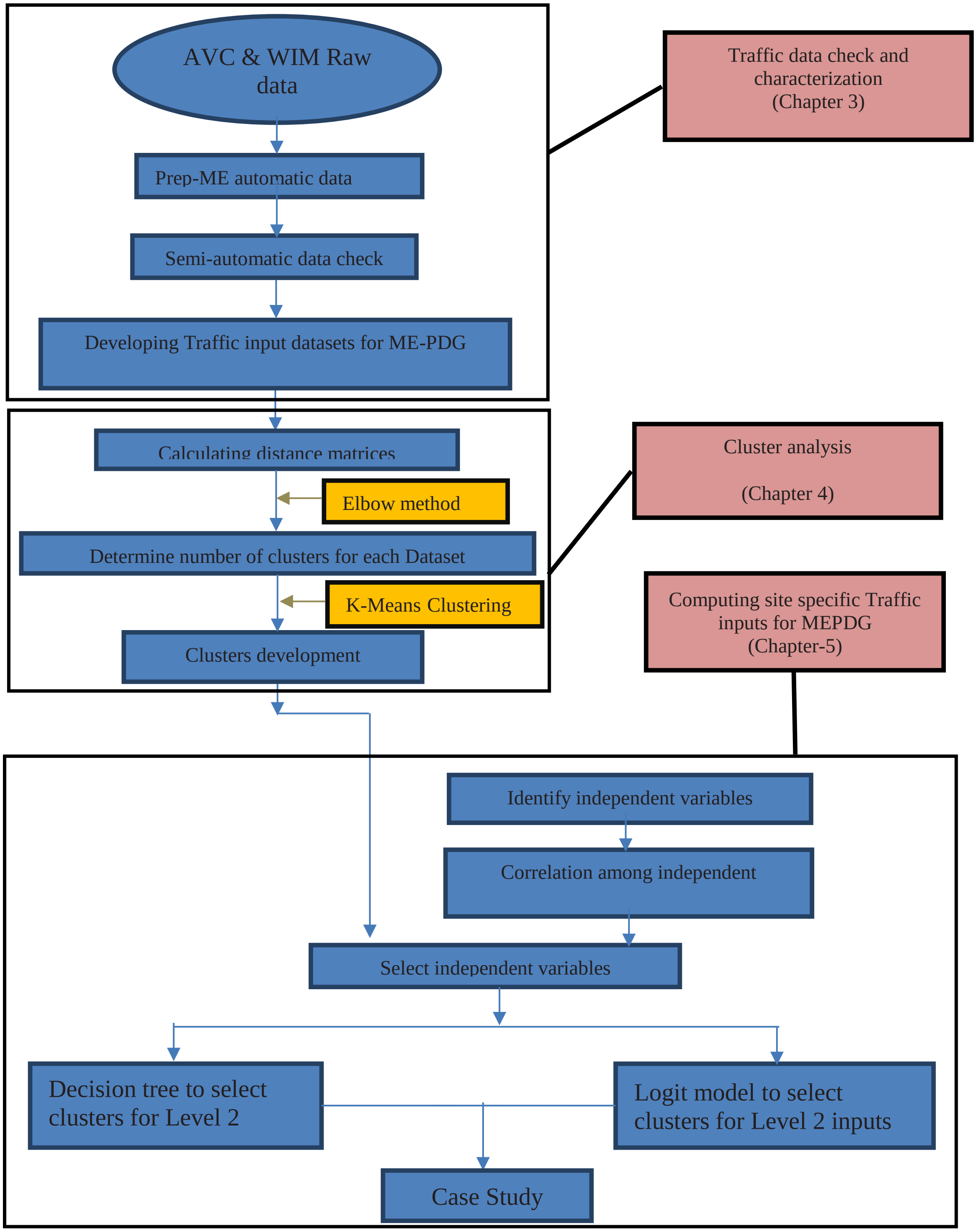


Figure 1.1 Flowchart of report outline

CHAPTER II

2 LITERATURE REVIEW

2.1 Pavement ME Design Procedure

The Pavement ME Design approach consists of three major stages (AASHTO, 2014). Stage 1 of this procedure is to develop input values and identify potential strategies or trial designs. Pavement materials inputs, traffic characterization data, and climatic data are developed and fed into the Pavement ME Design software. Stage 2 consists of the structural/performance analysis, in which the trial section is analyzed incrementally over time using the pavement response and distress models, and the outputs of the analysis are accumulated damage amounts of distress and smoothness over time. A pavement structural design is therefore obtained through an iterative process in which predicted performance is compared against the design criteria until all are satisfied with the specified reliability level. Stage 3 of the process includes the evaluation of the structurally viable alternatives, such as life-cycle cost analysis and constructability analysis.

The hierarchical approach is a unique feature in Pavement ME Design about traffic, materials, and environmental inputs, which provides the designer with flexibility in obtaining design inputs based on the criticality of the project and available resources. Level 1 inputs, generally regarding site-specific inputs, provide for the highest level of accuracy and would have the lowest level of uncertainty. Level 2 inputs provide an intermediate level of accuracy, typically would be user-selected either from an agency's database, a limited testing program, or estimation through correlations. Level 3 inputs provide the lowest level of accuracy. National default values provided in the Pavement ME Design software are generally used as level 3 inputs.

2.2 Traffic Input Levels

The equivalent single axle load (ESAL) approach used for traffic characterization in AASHTO 1993 version is no longer needed in the MEPDG (AASHTO, 1993). The MEPDG requires axle load spectra along with different types of distribution factors of various types of vehicles (AASHTO, 2014). Therefore, development of traffic input parameters is essential for successful implementation of MEPDG for design and analysis of new pavements and rehabilitation of existing pavements. The MEPDG uses a hierarchical approach (Level 1 through Level 3) for development of traffic input parameters. The Level 1 – Site Specific, Level 2 – State/Regional Specific and Level 3 – National/default, indicate a good, modest, and poor knowledge of past and future traffic characteristics, respectively.

Ideally, site-specific traffic data regarding traffic count, time distribution, axle configuration, and axle load spectra should be collected for each design project. This traffic data will provide the most accurate traffic input for the MEPDG design. However, such an effort is impractical, and the data are rarely available, due to the associated cost. A more rational practice would be using site-specific traffic data for especially important roads and regional- or national-default values for less important roads. Table 2 presents the data required at different input levels for all required traffic inputs in the MEPDG.

Table 2.1 Data Required for Three Hierarchical Input Levels (NCHRP 1-37A 2004)

Data Elements/Variables		Input Level 1	Input Level 2	Input Level 3
Truck Traffic and Tire Factors	Truck directional distribution factor	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Truck lane distribution factor	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Number of axles by axle type per truck class	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Axle and tire spacing	Hierarchical levels not applicable for this input		
	Tire pressure or hot inflation pressure	Hierarchical levels not applicable for this input		
	Truck traffic growth function	Hierarchical levels not applicable for this input		
	Vehicle operational speed	Hierarchical levels not applicable for this input		
	Truck lateral distribution factor	Hierarchical levels not applicable for this input		
	Truck monthly distribution factors	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Truck hourly distribution factors	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
Truck traffic distribution and volume variables	AADT or AADTT for base year	Hierarchical levels not applicable for this input		
	Truck distribution/spectra by truck class for base year	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Axle load distribution/spectra by truck class and axle type	Site specific WIM or AVC	Regional WIM or AVC	National WIM or AVC
	Truck traffic classification group for pavement design	Hierarchical levels not applicable for this input		
	Percentage of trucks	Hierarchical levels not applicable for this input		

Many researchers have reported that utilization of Level 3 (default) traffic input parameters may result in inconsistent and incorrect performance of a pavement design and analysis using the AASHTOWare-ME (Lu and Harvey 2006, Tran and Hall 2007a and 2007b, Swan et al. 2008, Elkins and Higgins 2008, Jiang et al. 2008, Buch et al. 2009, Li et al. 2009, Ishak et al. 2009 and 2010, Smith and Diefenderfer 2010, Haider et al. 2011, Romansochi et al. 2011, Stone et al. 2011, Selezneva et al. 2014). All of the studies above found significant differences between the default and site-specific values. Therefore, it was recommended that every state must develop Level 1 (site specific) and Level 2 (regional or cluster-based) traffic input parameters for successful implementation of AASHTOWare-ME.

2.3 Traffic Input Parameters

ME-PDG allows user to provide three level of traffic inputs based on the available traffic characteristics and the significance of the project. Level 1 is site specific with high level of accuracy and it is very expensive to obtain this data. Level 3 is statewide average traffic input, which does not provides effective results. Level 2 is regional specific, which can develop traffic inputs by performing cluster analysis based of short-term site-specific data and data from similar sites. This can be an efficient way of developing traffic inputs if site-specific data is not available. In this study, three major types of traffic inputs were developed for the ME-PDG software a) Vehicle Class Distribution Factors, b) Monthly Adjustment Factors, and c) Axle Load Spectra.

Vehicle Class Distribution Factor (VCD)

Vehicle Class Distribution Factors were developed using the vehicle classification guideline of the FHWA. FHWA divides all the vehicles traveling in the US highway in a total of 13 classes. In this study, VCD data of approximately 90 AVC stations and five years is used. This data is provided by ODOT. Only truck traffic (FHWA vehicle Class 4 through 13) is taken into consideration for the analysis and developing traffic inputs. Class 4 and Class 9 contributes the majority of truck traffic.

Monthly Distribution Factors (MDF)

The monthly distribution factor (MDF) represents the proportion of annual truck traffic for a given class of a vehicle that occurs in a specific month. In other words, the monthly adjustment factors for a specific month is equal to the monthly truck traffic for a given class for the month divided by the total truck traffic for that truck class for the entire year. Seasonal variation of truck traffic can be observed based on this parameter.

Axle Load Spectra (ALS)

The axle load distribution factors represent the percentage of total axle loadings within each load interval for a specific axle type. Definition of load intervals for different axle types is provided below:

- Single Axles: 3 kips to 40 kips, at 1 kip interval.
- Tandem Axles: 6 kips to 80 kips, at 2 kips interval.
- Tridem and Quadrem Axles: 12 kips to 102 kips at 3 kips interval.

Axle load spectra for four-axle types (single, tandem, tridem and quad) for all vehicles were developed using the WIM data form approximately 21 WIM stations of five years. Single axles and tandem axles contributes the majority of damage for the pavement.

2.4 WIM Data Quality and Data Check

ASTM E1318-09 (2009) defines weigh-in-motion (WIM) as "the process of estimating a moving vehicle's gross weight and the portion of that weight that is carried by each wheel, axle, or axle group or a combination thereof, by measurement and analysis of dynamic vehicle tire forces." It classifies WIM systems into four types based on their application and details their respective functional, performance, and user requirement. Table 1 lists functional performance requirements for each kind of WIM system.

Table 2.2 Functional Performance Requirements for WIM Systems

Function	Tolerance for 95 % Compliance[A]				
	Type I	Type II	Type III	Type IV	
				Value ≥lb (kg)[B]	±lb (kg)
Wheel Load	±25 %		±20 %	5000 (2300)	300 (100)
Axle Load	±20 %	±30 %	±15 %	12 000 (5400)	500 (200)
Axle-Group Load	±15 %	±20 %	±10 %	25 000 (11 300)	1200 (500)
Gross-Vehicle Weight	±10 %	±15 %	±6 %	60 000 (27 200)	2500 (1100)
Speed	±1 mph (2 km/h)				
Axle-Spacing and Wheelbase	±0.5 ft (0.15 m)				

[A] 95 % of the respective data items produced by the WIM system must be within the tolerance.
[B] Lower values are not usually a concern in enforcement.

There are a number of quality control (QC) procedures for WIM data check. LTPP (2013) provided mandatory, logic, range and verification QC checks on traffic data collected in the field before entry into the data base to guarantee data quality. LTPP (2001) developed traffic QC software to load, process, and produce reports for the LTPP program. FHWA (2013) and AASHTO (2009) guides are industry standards and emphasize the need for quality control measures in traffic monitoring programs. ASTM E2759-10 (2010) also disclosed how traffic data was managed from field data collection through evaluation, acceptance, summarization, and reporting. There are also state and project specific traffic data QC requirements, e.g., QC procedures developed to apply to New Mexico and North Carolina WIM data (Brogan et al., 2011, Ramachandran et al., 2011 and Stone et al., 2011), validation and QC checks for type I WIM traffic data to insure reliable and representative load spectra for MEPDG (Quinley, 2010), QC program for INDOT to improve the accuracy of WIM data to identify overweight vehicles (Nichols et al, 2004), and QC with peak-range check, peak-shift check and correlation analysis to quantify the axle loading spectra comparison process of rational checks (Mai, 2013).

Both the FHWA Traffic Monitoring Guide (FHWA, 2001) and AASHTO Guidelines for Traffic Data Programs (AASHTO, 2009) emphasize the need for QC measures in traffic monitoring programs. As a result, some quality control (QC) procedures have been developed for WIM data check. ASTM E2759-10 (2010) disclosed how traffic data was managed from field data collection through evaluation, acceptance, summarization, and reporting. The LTPP (2013) provided mandatory, logic, range and verification QC checks on traffic data collected in the field before entry into the database to guarantee data quality. Several states have developed specific traffic data QC requirements and procedures, such as Indiana (Nichols et al., 2004), California

(Quinley, 2010), North Carolina (Sayyady et al., 2010, Ramachandran et al., 2011), and New Mexico (Brogan et al., 2011).

In particular, the traffic data check procedure included in the FHWA Traffic Monitoring Guide (TMG) (FHWA, 2001) has been widely adopted. For vehicle classification data, a four-step data check procedure is recommended: (1) to compare the manual classification counts with the hourly vehicle classification data; (2) to check the number of Class 1 (motorcycles); (3) to check the reported number of unclassified vehicles; (4) to compare the current truck percentages by class with the corresponding historical percentages. No significant changes in the vehicle mix should be anticipated. For weight data check, there are two basic steps to evaluate recorded vehicle weight data (FHWA, 2001). Firstly, to check the front axle and drive tandem axle weights of Class 9 trucks. The front axle weight should be between 8,000 and 12,000 lb (10,000 ± 2,000 lb). The drive tandems of a fully loaded Class 9 truck should be between 30,000 and 36,000 lb (33,000 ± 3,000 lb). Secondly, to check the gross vehicle weights of Class 9 trucks. The histogram plot should have two peaks. One represents unloaded Class 9 trucks and should be between 28,000 and 36,000 lb (32,000 ± 4,000 lb). The second peak represents the most common loaded vehicle condition with a weigh between 72,000 and 80,000 lb (76,000 ± 4,000 lb).

Other procedures, primarily based on the FHWA TMG procedure but customized to individual states, have also been proposed by various researchers. For example, Mai. (2013) Developed a QC procedure including peak-range check, peak-shift check, and correlation analysis to quantify the axle loading spectra comparison process of rational checks. A structured quality control check procedure was suggested by Tarefder et al. (2013) for New Mexico to eliminate erroneous data.

2.5 Tools for WIM Data Analysis

With the wide use of WIM data for various applications, several tools have been developed to aid WIM data process and analysis. The BullPiezo software could compute Seasonal Adjustment Factor (SAF), Annual Average Daily Traffic (AADT), and Monthly Average Daily Traffic (MADT) from WIM data based on TMG (Kwon, 2015). TrafLoad, the final product of the NCHRP Project 1-39 project, can convert standard FHWA classification count and weight data files into vehicle classification, load spectra and traffic growth forecast to the 2002 AASHTO pavement design software without QC procedures (NCHRP 1-39, 2004). Prep-ME is developed to pre-process, import, check the quality of raw WIM traffic data, and generate the required three levels of traffic inputs for DARWin-ME software (Wang et al. 2013, and Wang et al. 2014). Long-Term Pavement Performance Pavement Loading User Guide (LTPP PLUG) software helped users select site-specific or default axle loading conditions from its traffic loading library and produced axle load distribution input files for the MEPDG or DARWin-ME software (Selezneva and Hallenbeck, 2013).

With the increasing use of WIM data for various applications especially for the Pavement ME Design in recent years, several tools have been developed to aid WIM data processing and analyzing. The BullPiezo developed software to compute AADT, seasonal and monthly adjustment factor from WIM data (Kwon, 2015). TrafLoad, the final product of the NCHRP 1-39 Project (NCHRP 1-39, 2004), can process standard FHWA classification and weight data for MEPDG but without data QC procedures and several data requirements for MEPDG not met. Many state highway agencies have developed Excel® spreadsheet-based tools to reduce raw vehicle classification and weight data, and to generate volume adjustment factors and axle load spectra for the Pavement ME Design (Tran et al. 2007a 2007b, Tarefder et al. 2013, Hasan et al.

2016). However, the quality control and updating procedure need to be repeated manually when new traffic data are available. In particular, LTPP developed a spreadsheet-based tool, named Pavement Loading User Guide (PLUG), to help users select site-specific or default axle loading conditions from its traffic loading library and produce axle load distribution input files (Selezneva and Hallenbeck, 2013).

The state pooled fund study TPF-5(242), Traffic and Data Preparation for AASHTO MEPDG Analysis and Design, has developed a full production software named Prep-ME to store and process climate, traffic, and materials data required for the Pavement ME Design Software. This software complies with FHWA TMG and Travel Monitoring Analysis System (TMAS) for quality control and quality check. State highway agencies' experience has been built into the QA/QC of traffic data collection. The software has the following key functions with more specific features requested by individual states (Wang et al. 2013, and Wang et al. 2014).

- Perform automatic quality control check by direction and by lane of a WIM station for both classification and weight data following the algorithms defined in TMG.
- Provide user-friendly interfaces to review monthly, weekly and daily traffic data, and investigate the WIM data that is incomplete or fails the automatic QC check through various manual sampling and analyzing operations.
- Generate three levels of traffic inputs that can be directly imported into the MEPDG and Pavement ME Design Software. Level 1 site-specific, Level 2 clustering average, Level 3 state average, and LTPP TPF-5(004) defaults. Clustering methods developed by North Carolina and Michigan DOTs, the Truck Traffic Classification (TTC) method and the simplified TTC approach are fully implemented offering state agencies the flexibility of generating Level 2 loading spectra inputs based on the availability of traffic data.

2.6 Traffic Data Clustering Analysis

Specifically, to generate Level 2 traffic inputs, many studies performed clustering analysis to identify typical axle load spectra for a region. Papagiannakis et al. (2006) applied hierarchical cluster analysis technique on LTPP WIM data to identify groups of sites with decreasing similarities based on either the vehicle percentage by class or the percentage of axles by load interval. Wang et al. (2007) conducted clustering analysis on the spatial and temporal variations of the load distributions from the LTPP traffic database. Wang et al. (2011) proceeded cluster analysis approach to identify loading patterns and estimation of full axle-load spectrum data using Arkansas WIM data. Sayyady et al. (2011) accomplished multidimensional clustering approach to generate regional average truck axle load distribution factors for North Carolina. Mai et al. (2013) considered the effects of traffic inputs on pavement design thickness and applied correlation-based clustering to determine the number of clusters objectively. Abbas et al. (2014) performed clustering analysis on WIM stations across the state of Ohio and evaluated site-specific, statewide average, cluster average, and MEPDG default axle load spectra traffic load effect on asphalt pavement design with the MEPDG. Li et al. (2015) employed the K-means cluster algorithm and developed simplified Truck Traffic Classification clusters for secondary road pavement design. Also, several state-specific clustering analysis methods were developed to incorporate their state-specific traffic characteristics for the Mechanistic-Empirical pavement design (Jiang Y. et al. 2008, Buch et al. 2009, Stone et al. 2011, and Wang et al. 2014).

Several states studied traffic data using rigorous cluster analysis to incorporate their state-specific traffic characteristics for the Pavement ME Design (Prozzi and Hong 2005, Lu and Harvey 2006, Jiang Y. et al. 2008, Lu and Harvey 2009, Buch et al. 2009, Ishak et al. 2010, Syyady et al. 2011, Haider et al. 2011, Darter et al. 2013, Tarefder 2013, Abbas et al. 2014a, 2014b, Wang et al. 2014). These research activities have simplified the understanding and applicability of traffic patterns.

CHAPTER III

3 TRAFFIC DATA CHECK AND CHARACTERIZATION

3.1 Prep-ME Software

Through the transportation-pooled fund study TPF-5(242), the Prep-ME software has been developed and enhanced based on extensive comments and feedback from participating states. The Pre-ME software is capable of importing the vehicle class distribution data and weigh-in motion data. This tool also provide automatic data quality check and exporting traffic data (Wang et al. 2013, and Wang et al. 2014).

3.2 Traffic Data Source

Currently, Oklahoma Department of Transportation (ODOT) operates approximately 90 Automatic vehicle classification stations, out of which 21 are also WIM stations (Oklahoma traffic characteristics report, 2009). Five years (2008-2012) of continues WIM data and vehicle classification data is provided by ODOT from the 21 WIM stations. Also, approximately four years (2013-2016) of additional AVC data is available for the analysis. All the 90 stations are located on one of the interstate highway, US highway or state highway spread throughout the state. Table3.1 describes the location of each WIM and AVC station along with the route and county details. Figure 3.1 is the map with AVC and WIM stations.

Table 3.1 Description of AVC and WIM station locations

Station ID	COUNTY	ROUTE	LOCATION
AVC001	Cleveland	SH-37	On SH-37, 1.70 miles W of I-35, in Moore
AVC002	Cleveland	US-77	On US-77, 1.10 miles S of SH-9, in Norman
AVC003	Cleveland	SH-9	On SH-9, 2.10 miles E of I-35, in Norman
AVC004	Canadian	SH-152	On SH-152, 0.55 miles W of SH-4, in Mustang
AVC005	Oklahoma	US-62	On US-62, 9.75 miles E of I-35, in Choctaw
AVC006	Oklahoma	SH-66	On 39th St (SH-66), 1.00 miles W of I-44, in Oklahoma City
AVC007	Oklahoma	I-40	On I-40, 2.00 miles W of I-44, in Oklahoma City
AVC008	Oklahoma	I-40	On I-40, 3.80 miles E of I-35, in Midwest City
AVC009	Creek	SH-66	On SH-66, 1.40 miles E of 81st St, in Sapulpa
AVC010	Tulsa	US-169	On US-169, 2.10 miles N of I-244, in Tulsa
AVC011	Tulsa	US-75	On US-75, 0.80 miles N of SH-117, in Jenks
AVC012	Tulsa	SH-266	On US-266, 0.40 miles E of US-169, in Tulsa
AVC013	Tulsa	SH-97	On SH-97, 3.00 miles S of US-412, in Sand Springs
AVC014	Tulsa	US-64	On US-64 (Memorial Rd), 1.10 miles S of the Creek Tpk
AVC015	Comanche	I-44	On I-44, 0.50 miles N of SH-7 (Lee Blvd), in Lawton
AVC016	Kay	US-60	On US-60, 0.60 miles W of I-35
AVC017	Jackson	US-62	On US-62, 3.50 miles W of US-283, in Altus
AVC018	Tulsa	US-64	On US-64, 0.38 miles W of 49th W Ave, E of Sand Springs
AVC019	Tulsa	I-44	On I-44, 200 ft W of Exit 236 (129th E. Ave)
AVC020	Oklahoma	I-35	On I-35, 500 ft S of the Grand Ave (SE 36th St) Bridge
AVC021	Muskogee	US-64	On US-64 , 2.39 miles N of SH-2, N of Warner
AVC022	Garvin	US-77	On US-77, 1.74 miles S of SH-19, in Pauls Valley
AVC023	Oklahoma	I-44	On I-44, 0.5 miles N of SW 29th St , in Oklahoma City
AVC024	Oklahoma	US-77	On US-77, 0.1 miles S of Britton Rd
AVC025	Tulsa	SH-51	On SH-51, 0.50 miles W of 145th Ave
AVC026	Oklahoma	I-44	On I-44, 0.40 miles E of Kelly Ave, in Oklahoma City
AVC027	Woodward	US-270	On US-270, 3.80 miles E of SH-34. SE of Woodward
AVC028	Love	I-35	On I-35, 0.10 miles N of the Red River Bridge at TX
AVC029	Bryan	US-69	On US-69, 5.30. miles S of SH-22, NE of Durant
AVC030	Muskogee	US-69	On US-69, 11.30 miles N of US-266, S of Muskogee
AVC031	Kay	I-35	On I-35, 0.10 miles S of the Kansas/Oklahoma SL
AVC032	Payne	SH-51	On SH-51, 3.50 miles E of SH-51C, W of Stillwater
AVC033	Grady	US-81	On US-81, 2.10 miles S of SH-37, S of Minco
AVC034	Garfield	US-60	On US-60 , 5.00 miles E of SH-45, N of Enid
AVC035	Okmulgee	US-75	On US-75, 3.80 miles N of US-62, in Okmulgee

Station ID	COUNTY	ROUTE	LOCATION
AVC036	Cotton	I-44	On I-44, 0.20 miles N of the Red River Bridge at the TX
AVC037	Washita	SH-152	On SH-152, 1.50 miles W of US-183, W of Cordell
AVC038	Woods	US-64	On US-64, 4.30 miles E of SH-144, W of Alva
AVC039	Kingfisher	SH-51	On SH-51, 2.60 miles E of US-81, E of Hennessey
AVC040	Payne	SH-33	On SH-33, 0.50 miles E of SH-18, W of Cushing
AVC041	Osage	US-60	On US-60, 4.90 miles E of US-177, E of Ponca City
AVC042	Craig	US-60	On US-60, 0.10 miles NW of SH-66, W of Vinita
AVC043	Craig	SH-66	On SH-66, 3.00 miles SW of US-60, W of Vinita
AVC044	Adair	US-59	On US-59, 2.50 miles S of SH-100, S of Stillwell
AVC045	Latimer	SH-2	On SH-2, 7.70 miles S of SH-31, N of Wilburton
AVC046	Murray	US-77	On US-77. 2.00 miles N of SH-7, N of Davis
AVC047	Lincoln	SH-66	On SH-66, 2.40 miles E of SH-18N, E of Chandler
AVC048	Jefferson	US-81	On US-81, 2.00 miles N of US-70, N of Waurika
AVC049	Jefferson	US-70	On US-70, 3.20 miles E of US-81, E of Waurika
AVC050	Hughes	SH-9	On SH-9, 6.00 miles E of US-75, E of Wetumka
AVC051	Pittsburg	US-270	On US-270, 8.00 miles W of US-69, NW of McAlester
AVC052	Coal	US-75	On US-75, 3.00 miles SE of SH-3, NW of Coalgate
AVC053	Seminole	SH-99	On SH-99, 2.10 miles S of US-270, S of Seminole
AVC054	Beckham	I-40	On I-40, 400 ft E of the Texas SL
AVC055	Grady	US-81	On US-81, 2.50 miles N of US-62, N of Chickasha
AVC056	Oklahoma	I-35	On I-35, 0.40 miles S of NE 10th St
AVC057	Major	US-60	On US-60, 3.50 miles N of SH-8, N of Fairview
AVC058	Texas	US-54	On US-54, 8.60 miles NE of US-64, NE of Guymon
AVC059	Texas	SH-3	On SH-3, 1.30 miles SE of SH-94, W of Hardesty
AVC060	Caddo	SH-9	On SH-9, 1.50 miles W of.SH-146, W of Ft Cobb
AVC061	Oklahoma	I-240	On I-240, 2.00 miles E of I-44, in Oklahoma City
AVC062	Choctaw	US-70	On US-70, 4.40 miles E of US-70B E of Hugo,vicinity Sawyer
AVC063	Tulsa	I-244	On I-244, 0.30 miles N of 23rd St OP
AVC064	Tulsa	I-244	On I-244, 0.40 miles E of Harvard Ave
AVC065	Oklahoma	SH-74	On Hefner Pkwy, 0.70 miles N of 63rd St Bridge,OKC
AVC067	Oklahoma	I-40	On I-40, 0.80 miles E of I-240
AVC068	Tulsa	US-169	On US-169, 0.35 miles S of 31st St
AVC069	Cleveland	I-35	On I-35, at S end of SE 89th Street Bridge
AVC070	Pottawatomie	SH-18	On SH-18, 1.62 miles N of I-40
AVC071	Oklahoma	SH-74	On SH-74, 0.32 miles S of Waterloo Rd
AVC072	Oklahoma	I-40	On I-40 Crosstown, EB 265 ft W of Shields Blvd OP
WIM001	Washington	US-75	On US-75, 6.30 miles S of US-60, S of Bartlesville

Station ID	COUNTY	ROUTE	LOCATION
WIM002	Murray	I-35	On I-35, 3.60 miles S of SH-7, S of Davis
WIM003	Oklahoma	I-240	On I-240, 2.57 miles E of I-35, in Oklahoma City
WIM005	Wagoner	US-69	On US-69, 6.50 miles S of US-412, S of Chouteau
WIM006	Okfuskee	I-40	On I-40, 1.00 miles W of US-75 South, E of Okemah
WIM007	Blaine	US-270	On US-270, 2.70 miles W of SH-8, W of Watonga
WIM009	Pontotoc	SH-3	On SH-3, 1.10 miles E of SH-1, in Ada
WIM010	Pittsburg	US-69	On US-69, 5.40 miles N of SH-113 S, N of McAlester
WIM011	Grady	US-81	On US-81, 2.46 miles S of US-81B S, S of Rush Springs
WIM016	Mayes	US-412	On US-412, 2.60 miles W of US-69, W of Chouteau
WIM021	Bryan	US-69	On US-69, 1.10 miles N of the Red River Bridge
WIM022	LeFlore	SH-112	On SH-112, 1.20 miles E of US-59, E of Poteau
WIM023	Major	US-412	On US-412, 2.10 miles W of SH-58, W of Ringwood
WIM025	Cimarron	US-287	On US-287, 5.60 miles N of SH-325
WIM027	Kay	I035	On I-35, 3.50 miles N of US-60, S of Blackwell
WIM028	Canadian	I-40	On I-40, 300 ft W of Gregory Road
WIM029	Sequoyah	I-40	On I-40, 0.96 miles E of US-64
WIM030	McClain	I-35	On I-35, 0.47 miles W of SH-74
WIM032	McCurtain	US-70	On US-70, 4.50 miles W of US-259
WIM104	Logan	I-35	On I-35, 0.50 miles N of Waterloo Rd
WIM114	Washita	I-40	On I-40, 1.46 miles E of SH-34
WIM118	Comanche	US-62	On US-62, 1.30 miles W of SH-115

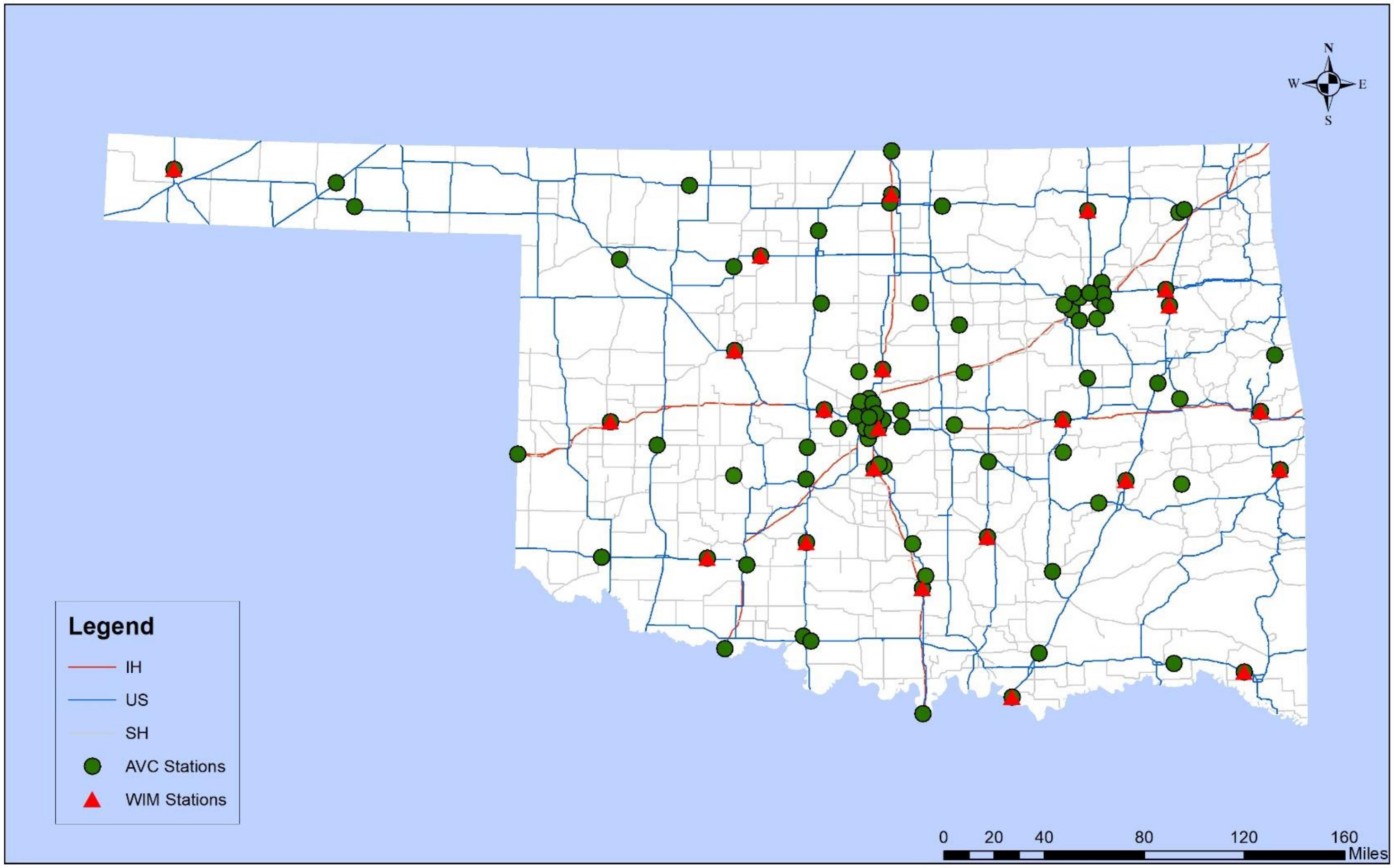


Figure 3.1 AVC and WIM Stations in Oklahoma

3.3 Statewide Traffic Data Check

The Prep-ME software is used to read the data WIM from the database and also as an efficient tool to perform statewide traffic data check. The quality check for the available data is performed in the following stages:

- Importing the Data into software with Travel Monitoring Analysis System (TMAS) check.
- Automatic Quality check.
- Manual review.
- Enhancing the Quality of data with few engineering judgments.

3.3.1 Importing Data into Prep-ME

The AVC and WIM data is imported by specifying the State name. Followed by Travel Monitoring Analysis System (TMAS 2.0) data check for each line of raw data, and report errors into an error log file for each imported file. Duplicate data and data with fatal and critical errors are not imported into the Prep-ME database. The software interface reports the number of rows of data importation, some records that failed the TMAS check, failure rate in percentage, and a number of rows that are duplicate in the data import. The number of failure records and its rate are recorded to assist traffic engineers to diagnose sensor issues. The data, which have passed the TMAS data, check and save them in the Prep-ME database tables. The Prep-ME user interface can provide information of few attributes like Station ID, Month, Year, Lane, direction and provides the graphical representation of vehicle class distribution, Gross Weight, Front axle load and Drive Tandem axle load distribution.

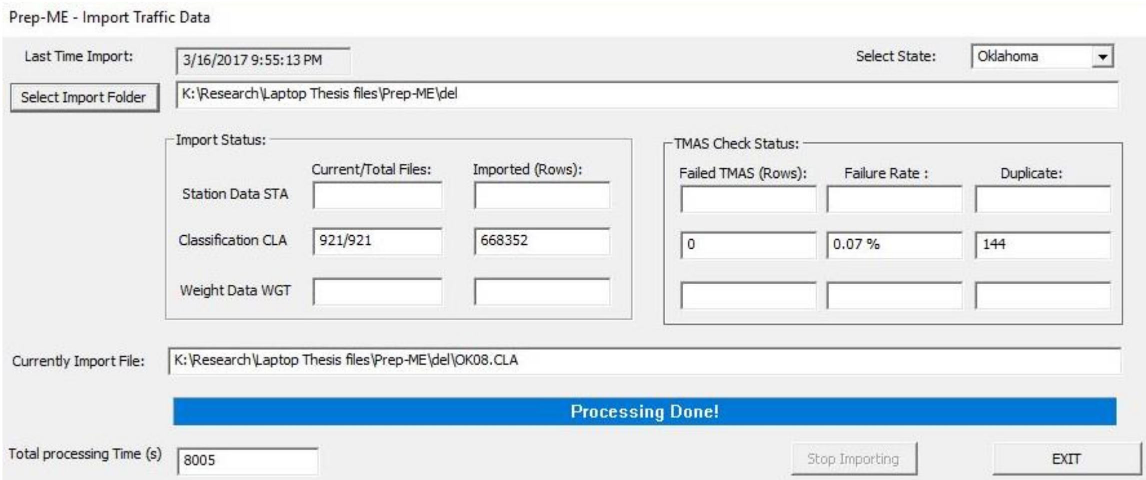


Figure 3.2 Importing ODOT WIM Data into Prep-ME Software

3.3.2 Automatic Quality Check

Prep-ME can check the data for all the provided specifications and automatically either accept or reject the data as a whole Station. In this process, three parameters define the quality of data.

- The proportion of Gross weight for Unloaded and Fully Loaded Truck Traffic.
- The range of Front Axle Load.
- The range of Drive Tandem axle weight for fully loaded Truck Traffic.

<u>Gross weight</u>

The Gross weight of a vehicle has a wide range of distribution (i.e., 4Kips to 140Kips). Every network has a maximum limit for the Gross weight based on their utility. Oklahoma has a maximum limit of 80Kips for the interstate highways.

In general, the proportion of vehicles for each weight distribution plot have two peaks. One of this represents the proportion of unloaded vehicles, and the other describes the fully loaded vehicles. In the process of the Automatic Quality check using Prep-Me, the range of Gross weight for unloaded vehicles and fully loaded vehicles is specified manually.

- The range for the Gross weight of unloaded (first peak): 28 - 36kips.
- The range for the Gross weight of Fully Loaded (second peak): 72 - 80kips.

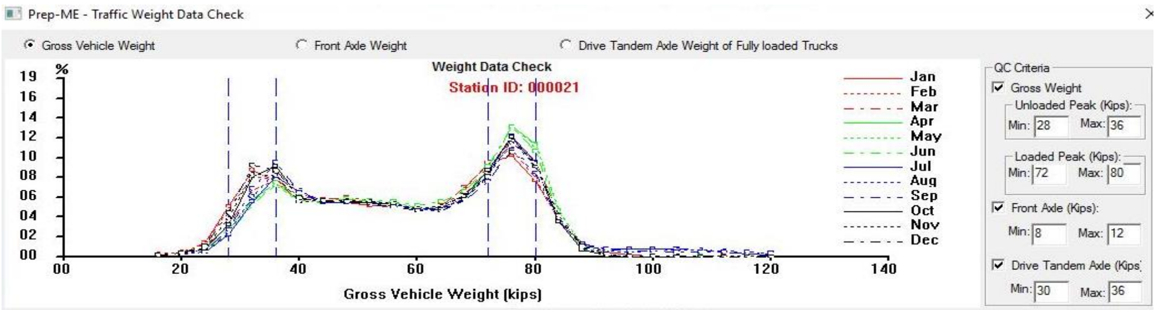


Figure 3.3 Gross Weight Distribution for Station WIM021

Front axle load

The front axle for most of the trucks should remain constant. Therefore, front axle weight has a low range of distribution. The quality check criteria are that weight should be distributed among the provided specific limits.

- Range for Front axle weight: 8-12kips

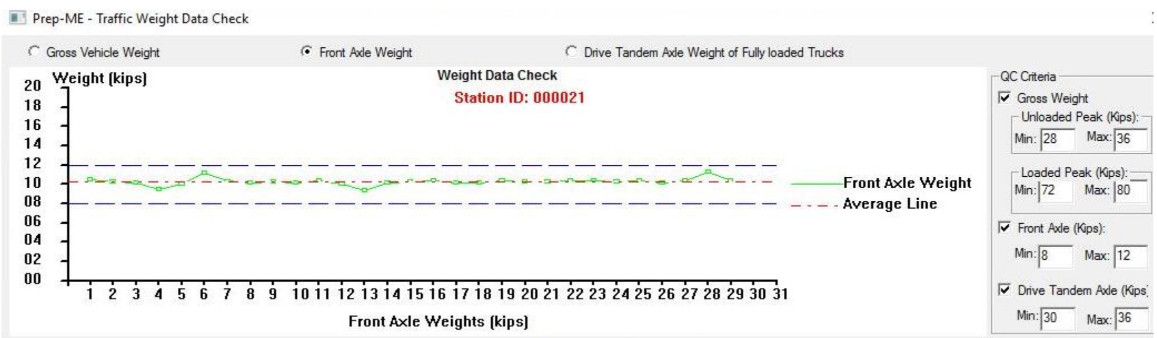


Figure 3.4 Front axle load distribution for Station WIM021

Drive Tandem axle weight for fully loaded Truck Traffic

The tandem axle weight of the fully loaded trucks has very high impact on the design life of the pavement. The load distribution has a significant variability. Each state DOT has a maximum limit for the tandem axle weight. Accordingly, the range is defined and specified to the Prep-ME for the automatic Quality check process.

- Specified range for Tandem axle weight of fully loaded Trucks: 30-36kips.

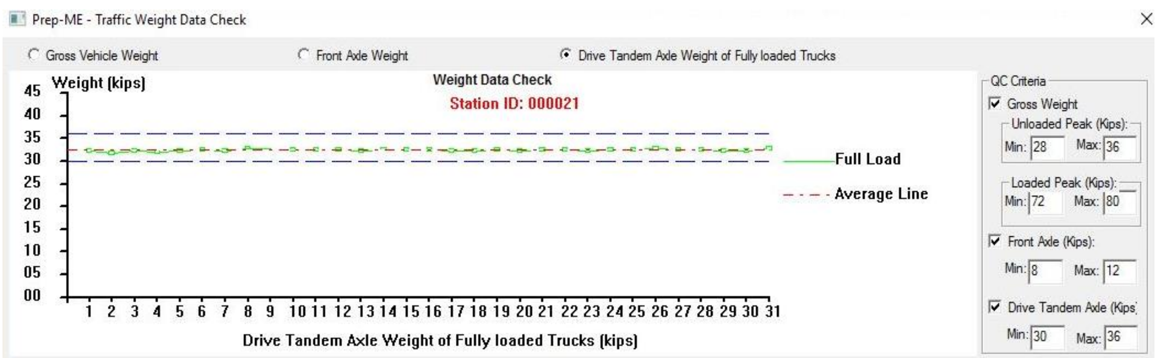


Figure 3.5 Tandem Axle Load Distribution for Fully Loaded Truck Traffic at WIM021

3.3.3 Semi-Automatic Quality Check

If those mentioned three parameters (Peak of the Gross weight for Unloaded and Fully Loaded Truck Traffic, range of Front Axle Load and range of Drive Tandem axle weight for fully loaded Truck Traffic.) are not within the specified limits, then the data set of the corresponding year, month and lane will be rejected automatically by the Prep-ME software. If all the four lanes of a particular month are rejected, then the month is rejected as a whole. If any month in a year got rejected by QC, then the corresponding year data will be considered as failed or rejected by QC.

After the automated quality check by the software, daily data for each month, which are rejected by software, are verified for three major parameters. They are

- Daily class 9 truck counts.

- Percent of front axle within TMG tolerance.
- Percent of tandem axle within TMG tolerance for fully loaded trucks.

Anyone of them might be a reason for the rejection of data during the quality check process. If the particular month of a station has very few class 9 trucks in the considered lane or major percent of front axle load or tandem axle load moving out of the specified TMG tolerance can be observed in rejected data.

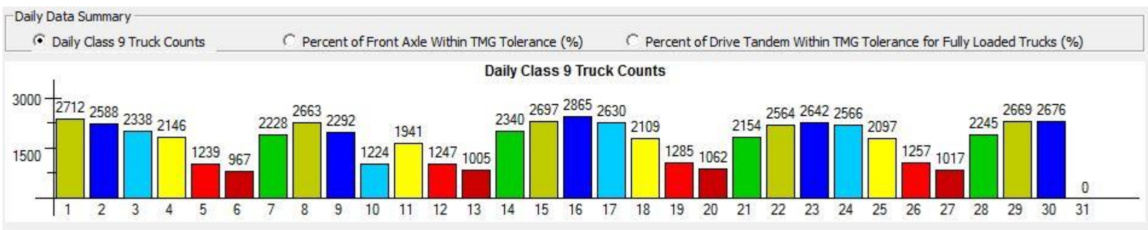


Figure 3.6 Daily Class 9 Truck Counts for month data at station WIM021

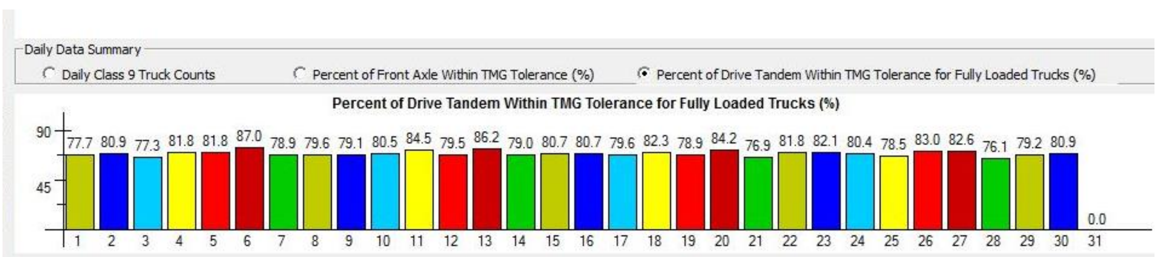


Figure 3.7 Percent of Front Axle within TMG Tolerance for month data at station WIM021

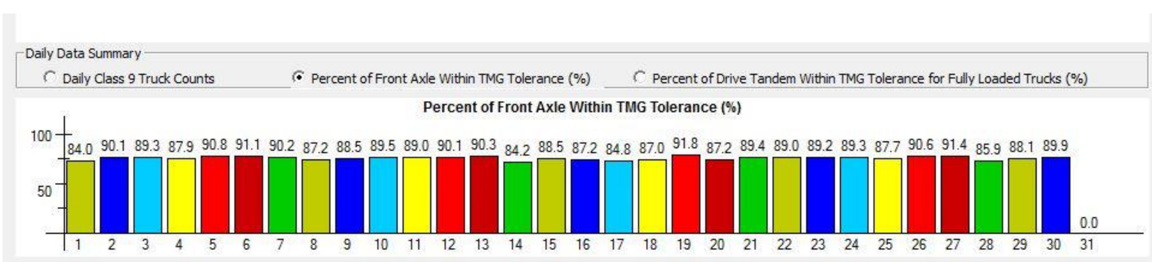


Figure 3.8 Percent of Tandem Axle within TMG Tolerance for Fully Loaded Trucks at WIM021

3.3.4 Engineering Judgements

After the review process, the reason(s) for the rejection of data is concluded. Prep-Me provides several tools that can perform specific modifications on the existing data sets. Based on the conclusion from the manual review one of the best suitable tools is used to enhance the quality of datasets. The major operations that can be performed at this stage are listed below.

- **Sampling a sub-dataset:** Sampling operation can be used as a diagnostic tool to investigate the reason(s) for bad data that cannot pass automatic data check, and weekly sample data with good quality to represent this month.
- **Replacing the dataset:** The data set is replaced if it cannot be sampled or if most of the data is lost. Replacement (copy and paste) can be used to check the similarity of the data in adjacent months, opposite direction, or different lane, same month but different year, and then identify a suitable month which can be used as the source to substitute the failed or missing month. For instance at station WIM001 the August month does not have data. So, that is replaced with the July month data shown in figure 3.8.

Figure 3.9 Replacing data in the process of QC at station WIM001

- **Manually Accepted:** If the data set is good and having the gross weight peak out of range, then the data set is manually accepted.

  If none of the cases happens then, it is represented as unmodified and unaccepted.

After the comprehensive quality check is performed, an example summary of the check is demonstrated. A complete summary is provided in the Appendix.

3.4 Analysis of Traffic Characteristics

This section of study provides brief description about the traffic characteristics that can be observed from the classification data and weigh-in-motion datasets. Few of them helps in better understanding about the station, as seasonal variation of truck traffic, direction distribution of trucks, time series variation in truck traffic patterns, expected daily truck traffic, presence of overloaded trucks, etc.

The following traffic characteristic parameters required in the Pavement ME Design are investigated for the time-series WIM data:

- Vehicle class distribution.
- Average daily truck traffic.
- Percentage of overload vehicles.
- Gross weight distribution spectrum.
- Tandem axle distribution spectrum.

3.4.1 Vehicle Class Distribution

Vehicle class distribution is the percentage distribution of vehicles according to the FHWA truck classification (i.e., Class 4 to class 13). Results of analysis performed at one of the WIM station is shown in figure 3.9. It is observed that Class 5 trucks and Class 9 Trucks contributes the majority of the truck traffic. Similar kind of results is observed even at rest of the WIM stations.

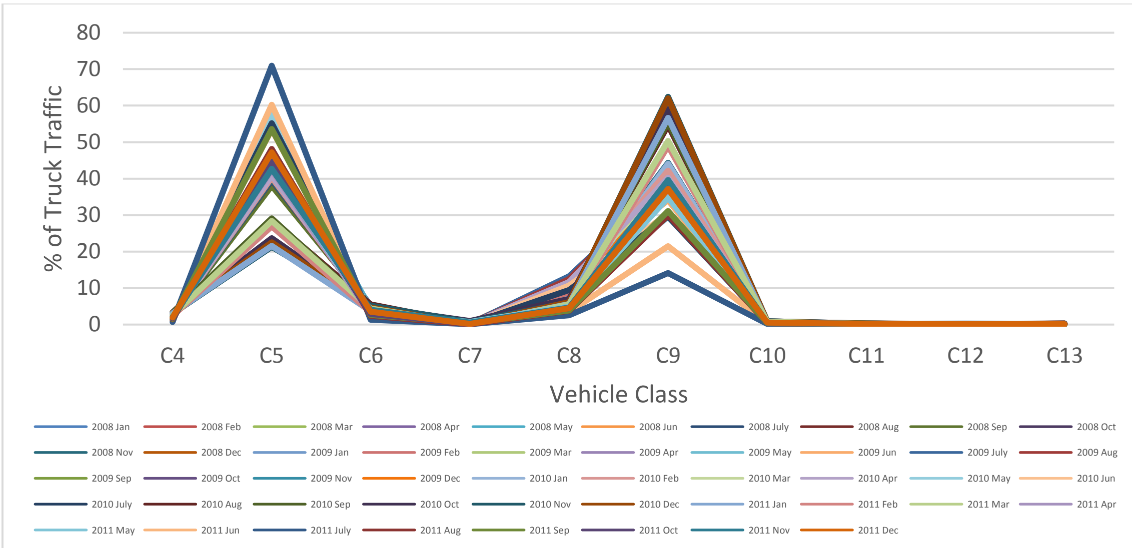


Figure 3.10 Vehicle Class Distribution for station AVC001

3.4.2 Average Daily Truck Traffic

The average daily traffic of each month in a year is combined and the variation among them is observed. Distribution at one of WIM station is represented in the Figure 3.10. It is observed there is a significant variation in the year 2010.

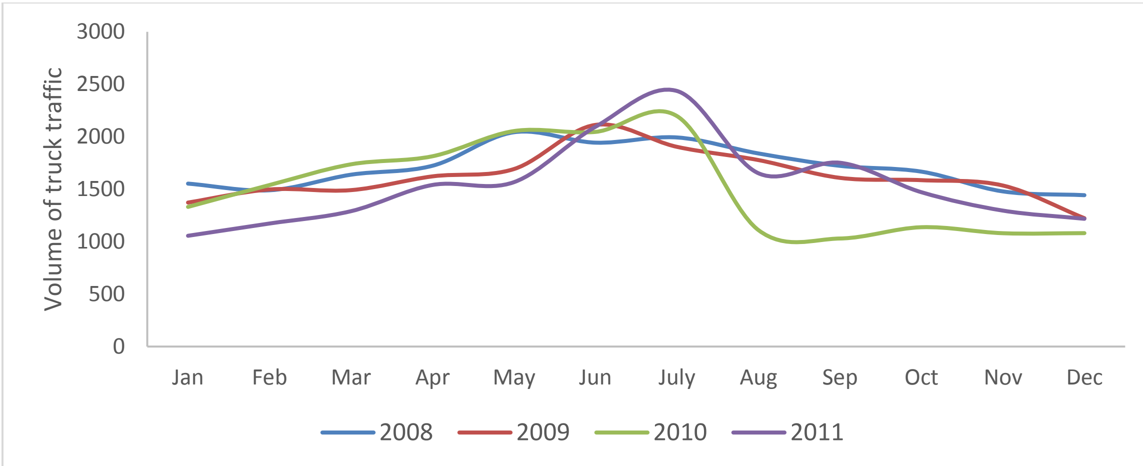


Figure 3.11 Average daily truck traffic distribution

3.4.3 Overload Vehicles

Percentage of vehicles that are overloaded are recorded and can be used to estimate the effect on the design of pavement. Observation at WIM021 station is shown in Figure.3.11. It was observed that there is no trend followed and the data has high variance but similar in both directions.

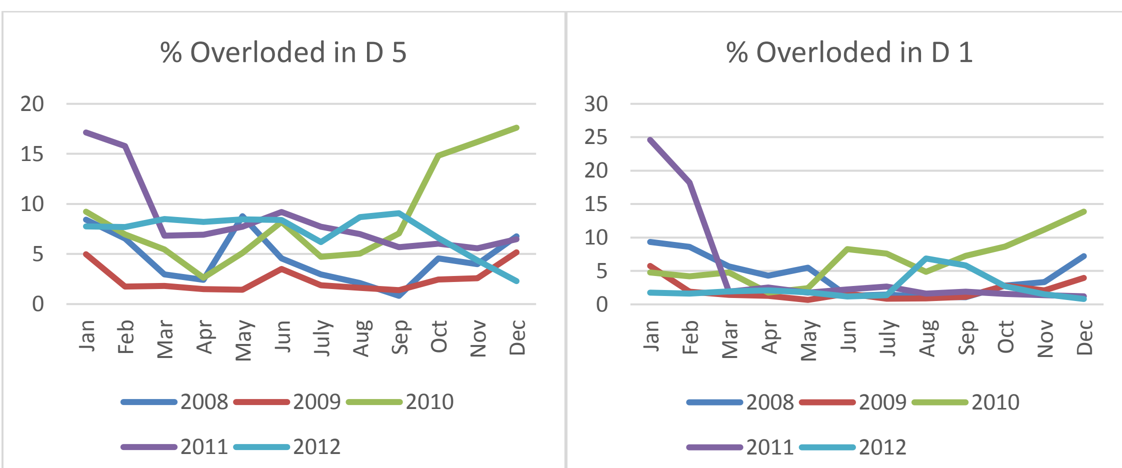


Figure 3.12 Percentage of vehicles overloaded at station WIM021

3.4.4 Gross Weight Distribution

Distribution of Gross weight of the vehicles is used as a traffic characteristic input by the MEPDG software. This distribution helps to calibrate the proportion of traffic having particular gross weight. At a WIM station, it is observed that gross weight was evenly distributed and the major proportion lies in between 28-36kips and 72-80kips. A similar trend is observed in the rest of the sites.

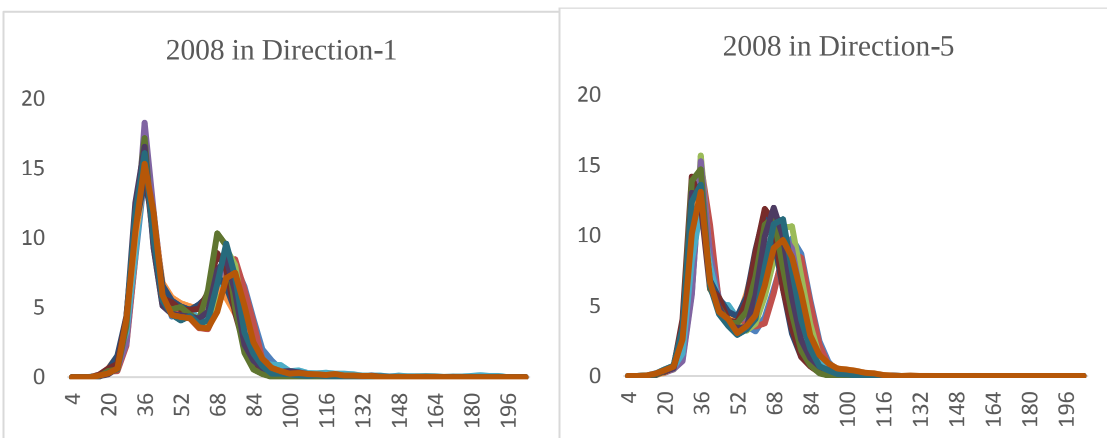


Figure 3.13 Gross weight distribution spectrum

3.4.5 Tandem Axle Distribution

Tandem axle weight has more impact on the design of pavement as it causes the major damage to the pavement. It was distributed widely among 4kips- 55kips. This major distribution portion of the traffic falls into two ranges, i.e., 6kips-18kips and 30kips-36kips. One of the WIM station has a similar distribution shown in Figure.3.13.

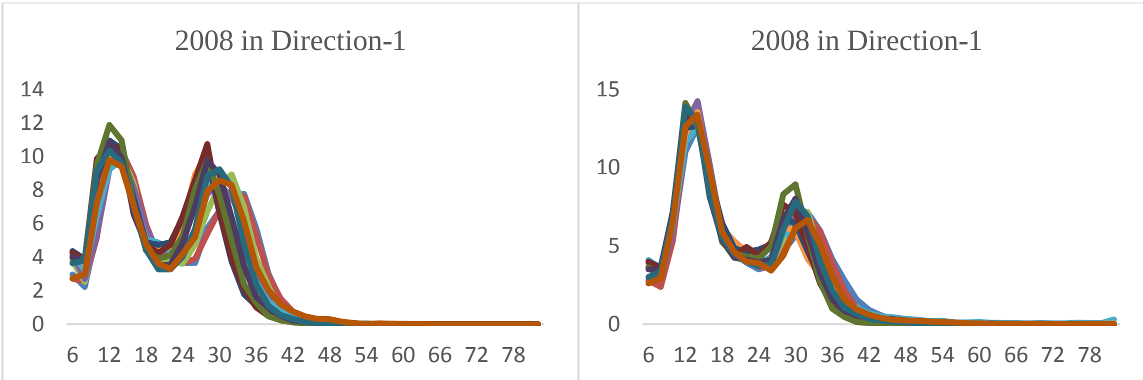


Figure 3.14 Tandem axle distribution spectrum

3.5 Traffic Data Preparation

After removing the QC outliers, missing data is identified and separated. Only data that passed the QC is considered for further analysis. The three major datasets are generated according to the required traffic input formats for Pavement ME design software.

- Vehicle Class distribution dataset (VCD): a two-dimensional vector with the percent of truck traffic for vehicle class (VC4 - VC13) for each month of five years at every station.
- Monthly distribution factor (MDF): as multiple vectors with percentage of truck traffic per each month in a year and similar vectors for each year at every station
- Axle loading spectrum (ALS): a multiple two-dimensional matrices of axle load distribution for single, tandem, tridem and quad axle types.

CHAPTER IV

4 TRAFFIC DATA CLUSTER ANALYSIS

4.1 Introduction

Site-specific information is not available throughout the state and Level 3 data is not reliable to predict accurate traffic patterns in all the cases. Therefore, the purpose of generating Level 2 traffic inputs is to identify the similarities in the time-series traffic patterns and classify them into groups. This process can reduce the number of possibilities of patterns for each traffic input parameter. Cluster analysis has been widely used for such purpose to identify homogenous groups of objects as clusters. Several techniques are available to perform cluster analysis, such as hierarchical technique (Papagiannakis et al., 2006, Wang et al., 2011, Li et al., 2016), multidimensional clustering approach (Sayyady et al., 2011), K-means algorithm (Li et al., 2015, Li et al., 2016), model-based (Li et al., 2016), and fuzzy c-means algorithms (Li et al., 2016). These research activities have simplified the understanding and applicability of traffic patterns and ultimately eased the preparation of the traffic load spectra inputs based on AVC and WIM data for the Pavement ME Design procedure.

4.2 Cluster Analysis Methodology

The process of developing clusters involves three major steps (Wang et al., 2011). First, is to construct a distance matrix for each traffic input parameter followed by determining the optimum number of cluster for that particular parameter. Finally, select an algorithm to define clusters.

4.2.1 Distance Matrix

To quantify the dissimilarity within datasets, a distance matrix is constructed for each matrix VCD, ALS, and MDF using Euclid distance technique. The distance matrix is a measure of dissimilarity among vectors. Considering data matrix X(nxm) with n measurements and m variables, can result in a matrix D(nxn) (Li Q et al., 2015).

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ \vdots & d_{22} & & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix}$$

The values are calculated by using Euclidean distance. Higher the value lesser the similarity among those vectors (Li Q et al., 2015).

$$d_{ij} = \|x_i - x_j\|_r = \left\{ \sum_{k=1}^{p} |x_{ik} - x_{jk}|^r \right\}^{1/r}$$

4.2.2 Optimum Number of Clusters

A number of clusters should be neither too high (fails the purpose of clustering) nor too low (loses the significant variations or patterns). So optimum number of clusters is to be determined. A number of clusters at which adding another cluster does not explain significant variation is considered as an optimal number. Elbow method is used to determine the optimal number of clusters or K-value, in which the total sum of squares within a cluster is plotted against the number of clusters. The change in slope is observed, and significant change (flattens) is considered as optimum K-value (Somi M, 2012).

4.2.3 K-Means Clustering

K-means clustering technique is performed to identify the clusters among datasets. This process starts with K-random vectors that act as centroids, around which clustering of each vector to the nearest one is observed, and then the mean of each cluster is considered as the new centroid. This process continues till the mean becomes the centroid of the cluster. This sequence of procedure to obtain clusters is called Lloyd's algorithm. However, the K-value, i.e., a number of clusters are to be determined initially (Soni M, 2012).

Both station level data and month level data are taken into consideration for the further analysis. Month level data can explain the impact of independent traffic characteristics on clusters and station level data can help in better understating the influence of geographic and demographic features on clusters.

4.3 Cluster Analysis based on Monthly Data

Considering monthly data for cluster analysis can account the seasonal variation of truck traffic also the truck-loading patterns. So, twelve months of five years data from all stations are used to develop clusters. For example, in station AVC001 percentage of class 5 trucks is significantly higher, but rest of the year proportion of class 5 trucks is similar to the class 9. To account this kind of variation monthly level clusters are developed.

4.3.1 Vehicle Class Distribution

Based on Elbow method the optimum number of clusters for the VCD matrix is considered as three. K-mean clustering is performed to identify those three clusters. Datasets having a higher proportion of class 9 trucks are grouped as cluster-1. A Higher fraction of class 5 trucks is observed in Cluster-2. Approximately similar percent of class 5 and class 9 trucks are clustered as the third one.

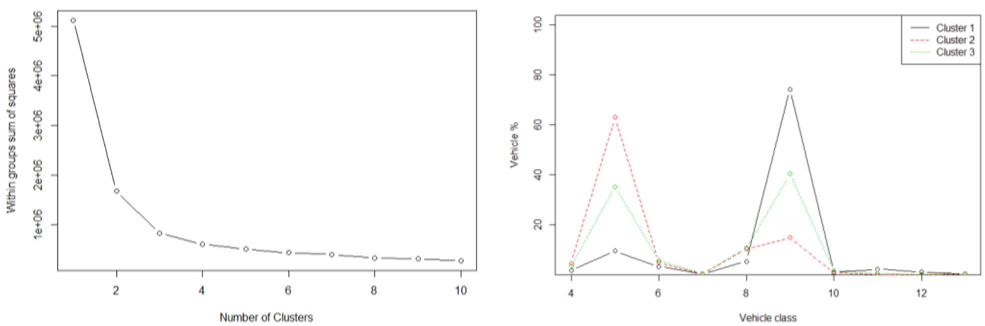


Figure 4.1 Clusters for monthly VCD data

4.3.2 Monthly Distribution Factor

Similarly, total sum of squares is plotted against the number of clusters. The significant change in slope is observed at three, four and five number of clusters. Clustering is performed on the matrix for three, four and five clusters. However, there is no significant variation recorded or observed from three to four clusters. So, K-value is considered as three for the MDF matrix. Cluster-1 consists of datasets having pretty consistent truck traffic throughout the year. Datasets having a higher proportion of truck traffic in March through June are grouped as Cluster-2. The third cluster explains the datasets have higher truck traffic in the months June through September.

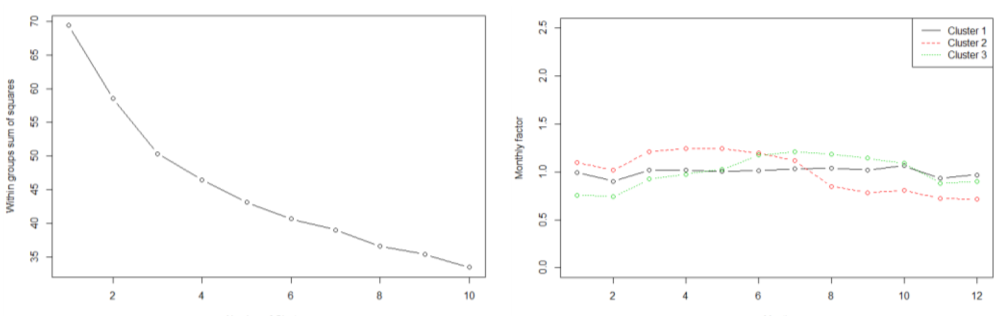


Figure 4.2 Clusters for monthly distribution factor

4.3.3 Axle Loading Characteristics

Datasets are analyzed separately as two-dimensional matrices for single, tandem, tridem and quad axle loading spectrum. Observations of the analysis are summarized below.

Single Axle Loading

While K-mean clustering is performed for single axle loading spectrum, resulting two clusters. Cluster-1 higher proportion of light axles (unloaded trucks). Cluster-2 is having a higher volume of heavy single axles.

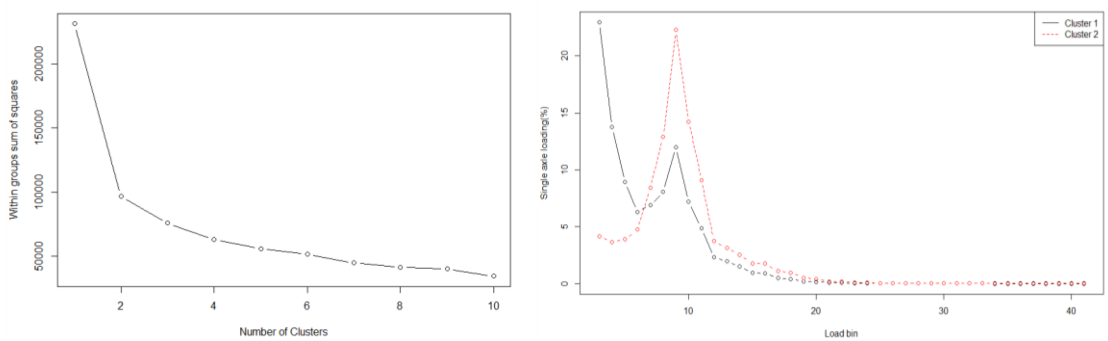


Figure 4.3 Clusters for monthly single axle loading spectrum data

Tandem Axles

Tandem axle loading spectrum matrix is analyzed in Elbow method, which results in a significant change of slope at three and four clusters. Based on the k-means method three clusters provides optimum variation within the dataset. Cluster-1 has slightly heavier axles. Cluster-2 consists of both light and heavier axles. Cluster-3 is made of more proportion of lighter axles.

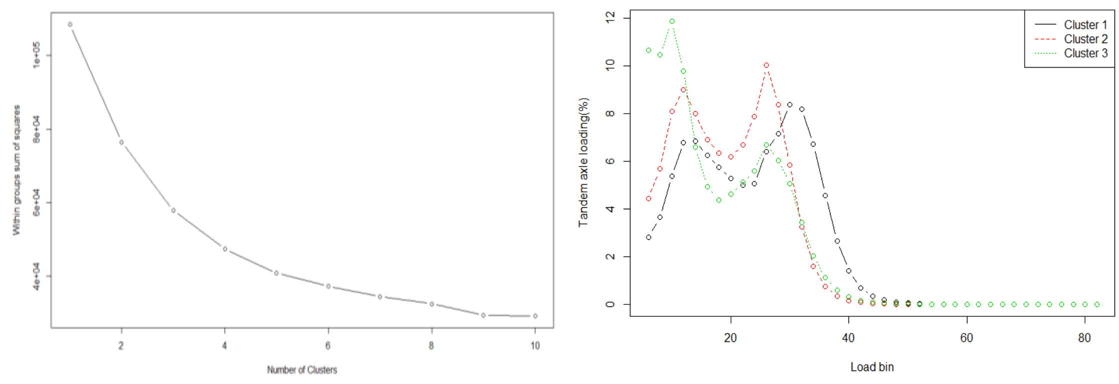


Figure 4.4 Clusters for monthly Tandem axle loading spectrum data

Tridem Axles

Cluster analysis is performed for three clusters on tridem axle spectrum dataset. Cluster-1 indicates the presence of light axles in the larger portion. Cluster-2 indicates the presence of both lighter and heavier axles. In Cluster-3 overloaded axles are observed.

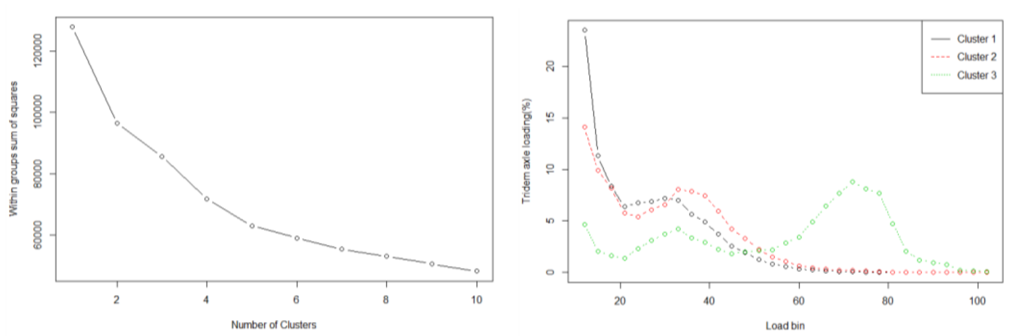


Figure 4.5 Clusters for monthly Tridem axle loading spectrum data

Quad Axles

The slope of the curve plotted for the sum of squares falls at three clusters. From the K-mean clustering, Cluster-1 is formed with a higher proportion of heavier Quad axles. Cluster-2 is grouped with a higher percentage of lighter axles. Cluster-3 is having a similar proportion of lighter and heavier axles.

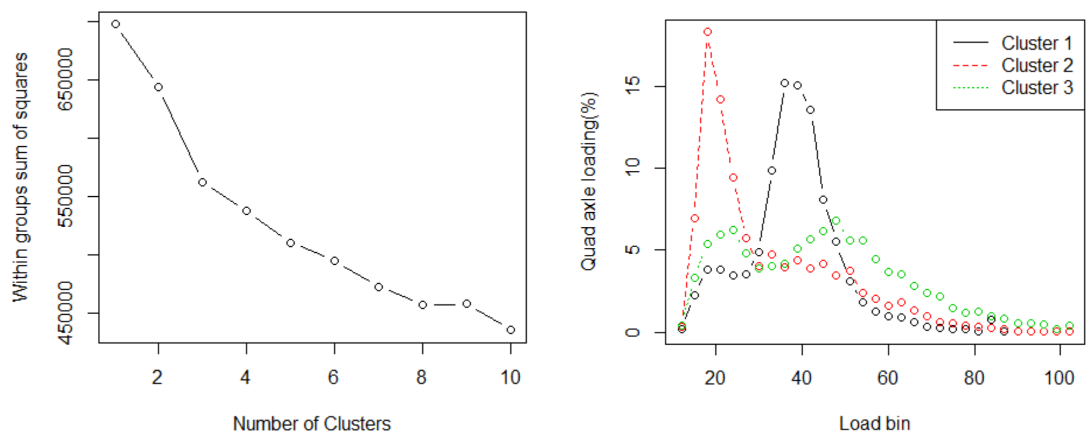


Figure 4.6 Clusters for monthly Quad axle loading spectrum data

4.4 Cluster Analysis based on Station Level Data

Clusters developed from the station level data might not be able to account for seasonal variations but this can in understanding the station characteristics, geographical spread of clusters, also can infer the influence of demographics on clusters and traffic patterns.

The similar way of clustering procedure is used to study the station level data. The three clusters obtained from the K-mean clustering of VCD data are representing cluster-1 stations having a higher proportion of class 9 trucks, cluster-2 had a dominant fraction of class 5 trucks, and the cluster-3 has a similar percent of class 5 and 9 trucks. Single axle loading also categorized into three clusters one having a major proportion of lighter axles, another with heavier axles and the third with both lighter and heavier axles. Even based on tandem axle spectrum stations are classified into a predominance of heavier, lighter and fewer weight axles. Finally, based on Tridem axle loading pattern stations are classified into significance proportion of lighter tridem axles, heavier tridem axles, and overloaded tridem axles.

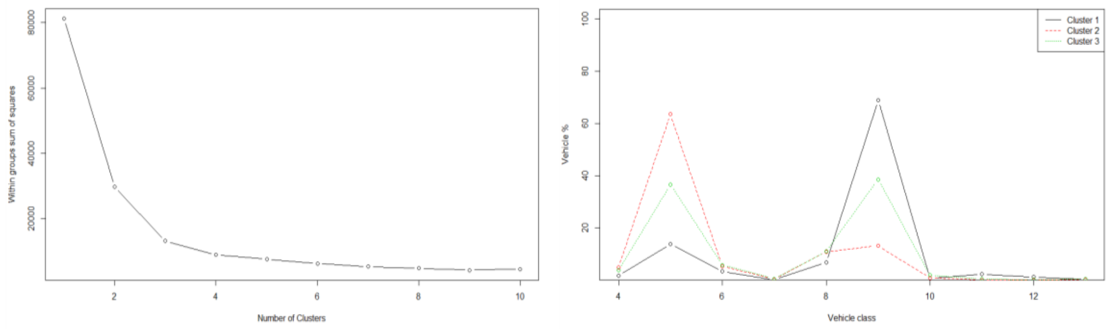


Figure 4.7 Clusters for station level VCD data

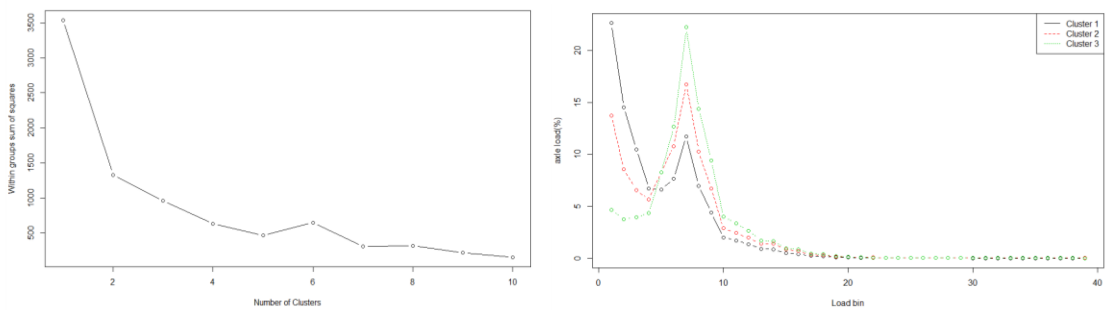


Figure 4.8 Clusters for station level single axle loading spectrum

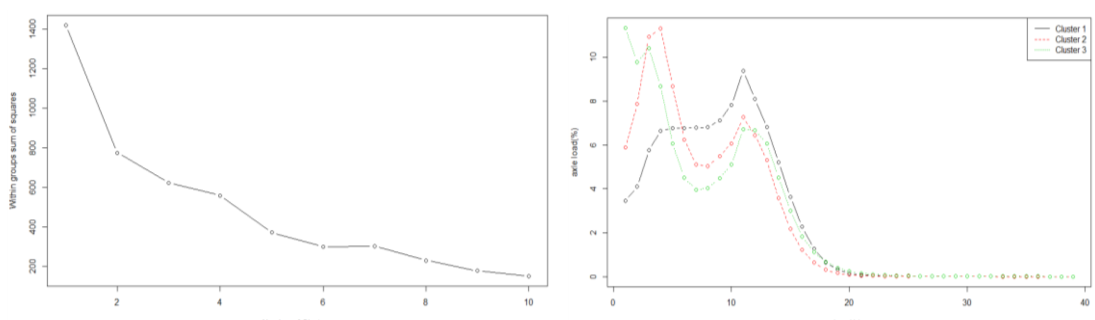


Figure 4.9 Clusters for station level Tandem axle loading spectrum

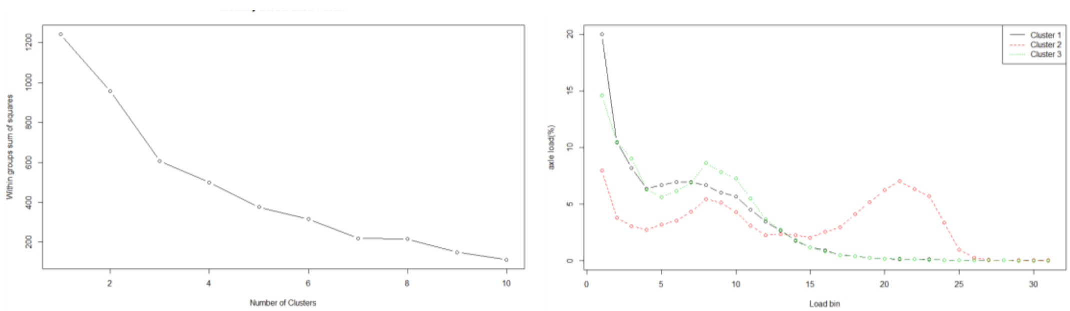


Figure 4.10 Clusters for station level tridem axle loading spectrum

When all the three-axle types are observed together, stations have higher percentage of heavier tandem axles also have greater proportion of fully loaded single Stations with greater number of lighter single axles also have higher percentage of lighter tandem axles.

Table 4.1 Summary of axle loading cluster groups

Axle type	Cluster group			
Single	3	1	2(a)	2(b)
Tandem	1	2(a)	2	3
Tridem	1	3	2(b)	1,3

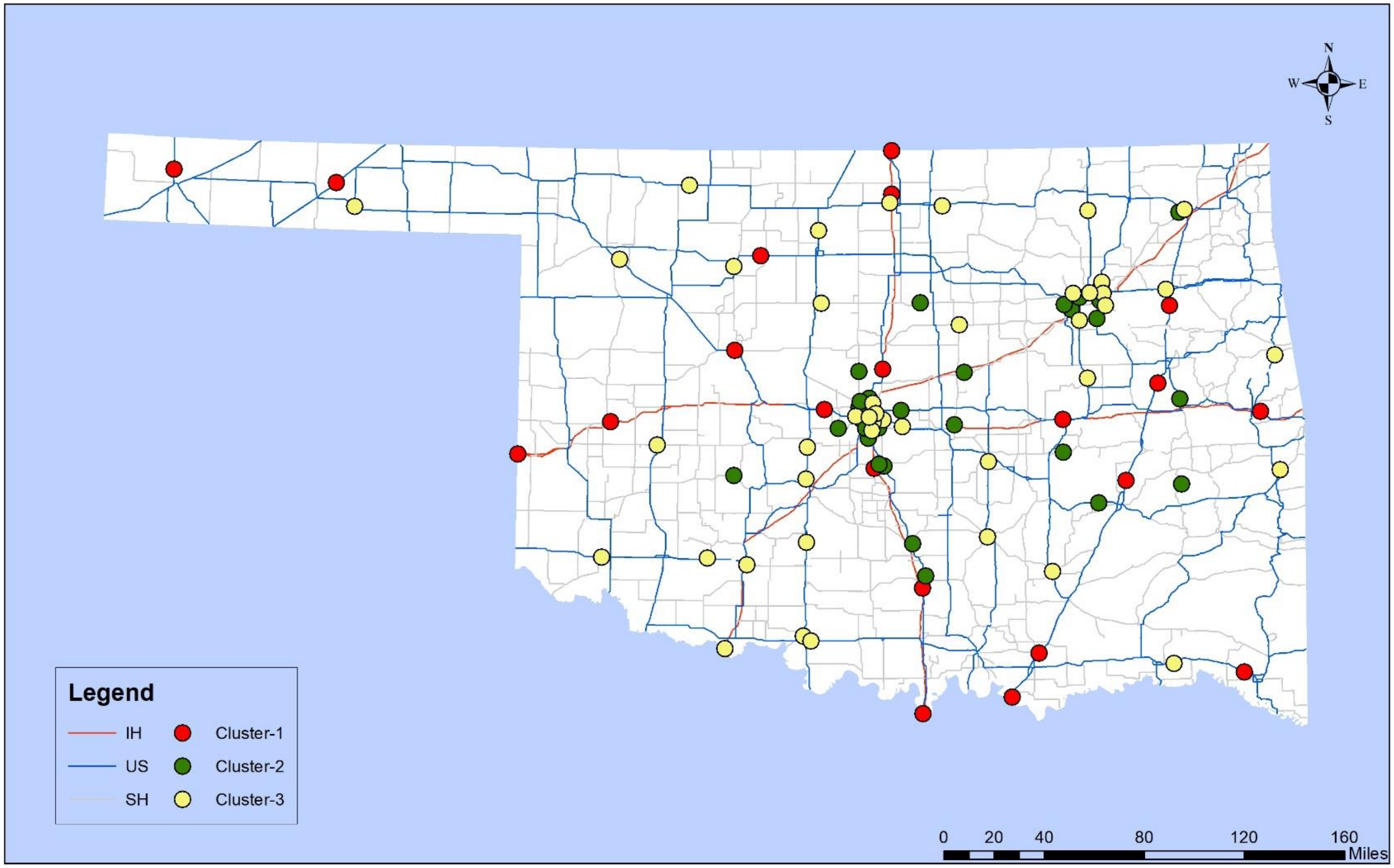


Figure 4.11 VCD clusters for Station level data

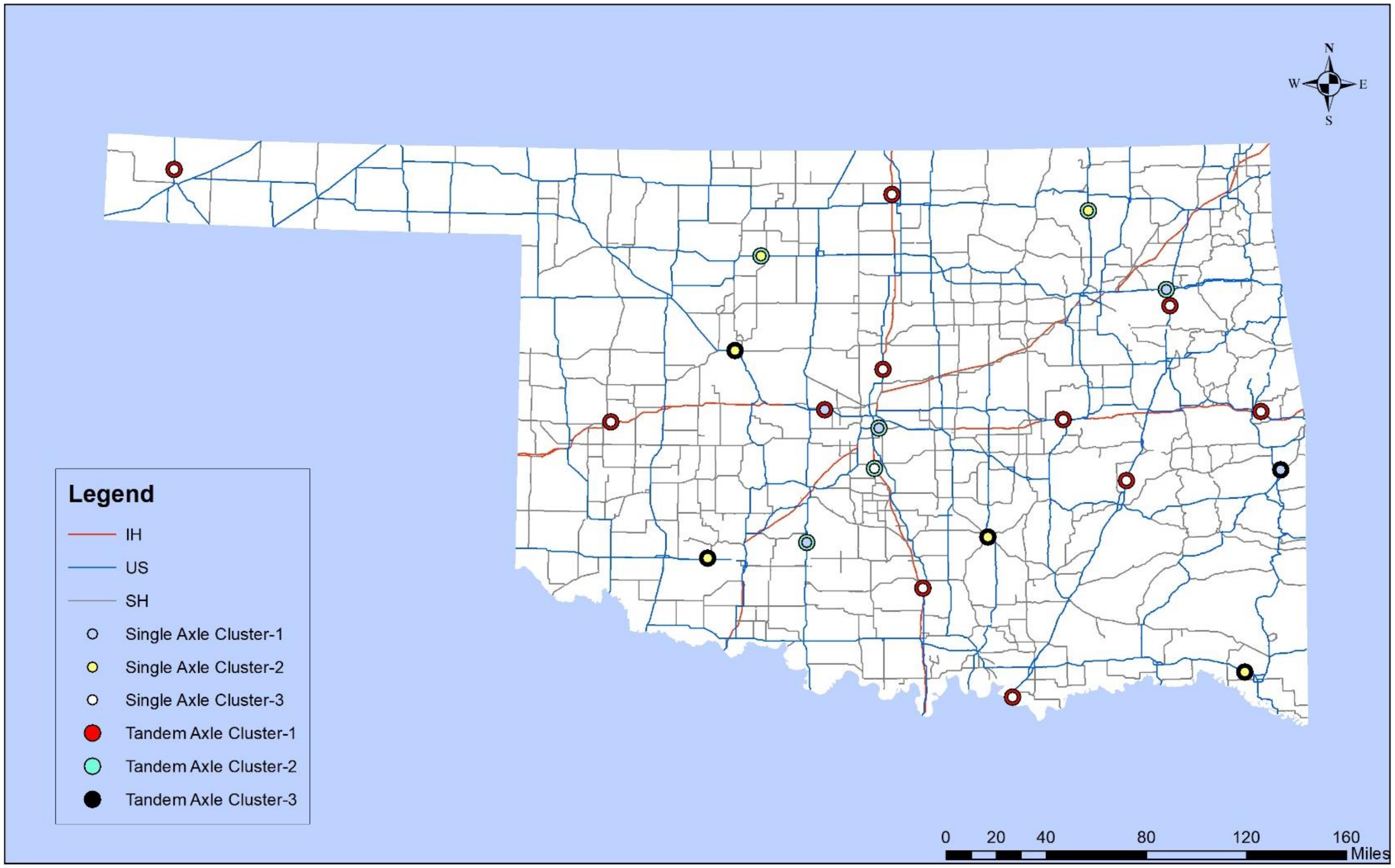


Figure 4.12 Axle loading clusters for Station level data

CHAPTER V

5 ESTIMATING LEVEL 2 TRAFFIC INPUTS FOR ME-PDG

5.1 Introduction

In order to generate Level 2 traffic inputs while no site-specific information is available and Level 3 is inadequate, Level 2 clustering input should be prepared. Identifying and defining the clusters is described in Chapter 4. In this Chapter, the goal is to develop decision models based on independent variables for selection of suitable traffic input cluster at the given site. This can be possible only if the model can be trained by the existing site-specific traffic input clusters and corresponding independent variables. Thus far, there are several methodologies have been implemented, including decision tree models, support vector machine models, adaptive neuro fuzzy inference system, regression models etc. (Pradhana, B et al., 2009).

In this study, two approaches are particularly investigated. One is decision tree based on month level clusters. Decision tree model can explain, visualize the cluster determination based on each independent variable. The other method is multinomial logit regression model using month level clusters, which can perform regression analysis by considering both discrete, continues data and provides the relative probability of determining one cluster over other. The methodology adopted to develop these models is explained in details. In addition, the spatial and geographical pattern of station-level clusters is presented for the level-2 traffic inputs as Figure 4.11 and Figure 4.12.

5.2 Selection of Independent Variables

Based on the literature review (Haider, S et al., 2011) AADTT, Truck traffic percentage (% TT), ratio of class 5 trucks to class 9 trucks (VC5/VC9), ratio of single unit trucks (class 5 through class 8) to multiple unit trucks (class 9 through class 13) (SU/MU), rural/urban and functional classification are considered as independent variables that may influence the clustering of both vehicle class distribution and monthly distribution factor. In addition to the variables mentioned above, upon investigating the pattern of Axle loading spectrum clusters, observed significant relation with a fraction of single axles to the tandem axles.

By observing the correlation among identified independent variables, no two independent variables that are highly correlated can be considered together in a single model. The interpretation of the correlation matrix is described below for each variable.

- The rural or urban classification, Function class of highway, average truck traffic volume and truck traffic percentage does not have highly correlation with any other variable. So, all of them can be consider as independent variables.
- However, percentage class 5 trucks are highly correlated with percentage class 9, the ration of class5 to class 9 and ratio of a single unit to multiple unit trucks. So, no two of them should come together as independent variables. Therefore, ratio of Single unit trucks to multiple unit trucks is considered as the fifth independent variable.

Table 5.1 Correlation matrix for independent variables

	Rural/ Urban	FC	VC5%	VC9%	VC5/VC9	SU/MU	MADTT /Volume	%TT
Rural/Urban	1.00							
FC	0.28	1.00						
VC5%	-0.19	0.44	1.00					
VC9%	0.20	-0.47	-0.95	1.00				
VC5/VC9	-0.23	0.38	0.71	-0.65	1.00			
SU/MU	-0.23	0.42	0.83	-0.78	0.91	1.00		
MADTT/Volume	-0.48	-0.46	-0.23	0.24	-0.21	-0.21	1.00	
%TT	0.45	-0.21	-0.42	0.45	-0.35	-0.41	0.05	1.00

5.3 Decision Tree Analysis

The objective of decision tree is to define set of rules for independent variables to define a dependent variable. Decision tree is a hierarchical model developed with set of procedure that splits dependent variables into homogeneous groups. If the data is continues then decision tree can be a regression model. If the variables are discrete, then the classification decision tree is effective. Wide ranges of tools are available to perform recursive partitionings, such as classification and regression tree (CART), chi-square automatic interaction detector decision tree (CHAID), ID3 classification algorithm and C4.5 (Biswajeeth, P et al,. 2013). R is a platform, which provides a package ‘part’ to compute classification and regression trees. As mentioned classification tree based models are efficient for categorical data, classification tree algorithm is used to build the decision trees in our analysis.

In the process of building a decision tree, we need to set the parameter ‘Complexity’ (cp) which reflects the number of splits (number of branches in the tree). Complexity is the representation of overall lack of fit. It ranges from 0 to 0.5, lesser value of complexity represents the higher number of splits and accuracy. The same package can provide the summary of data including a fraction of error, relative error and standard deviation for that particular complexity factor and number of splits. The complexity factor is determined based on the accuracy we required and the number of splits. It is not efficient to have more number of splits for a small decrease in error. Therefore, the optimum complexity is considered to build the decision tree. Along the decision tree, the package also can rank each independent variable with the percent of its influence on the determining cluster (Maechler, M et al., 2009).

5.3.1 Decision Tree for VCD

Table 5.2 Summary of decision tree for monthly VCD data.

CP	n-split	relative error	x-error	x-std
0.497	0	1.000	1.000	0.012
0.401	1	0.503	0.504	0.012
0.004	2	0.102	0.108	0.006
0.002	5	0.092	0.102	0.006
0.002	11	0.076	0.092	0.006
0.002	13	0.072	0.088	0.006
0.002	16	0.065	0.087	0.006
0.001	19	0.060	0.083	0.005
0.001	24	0.055	0.080	0.005
0.001	29	0.051	0.081	0.005
0.000	33	0.048	0.079	0.005
0.000	34	0.048	0.079	0.005

Table 5.3 Rank of independent variables in determining cluster for monthly VCD data.

SU.MU	%TT	AADTT	FC	Rural/Urban
65	17	9	8	1

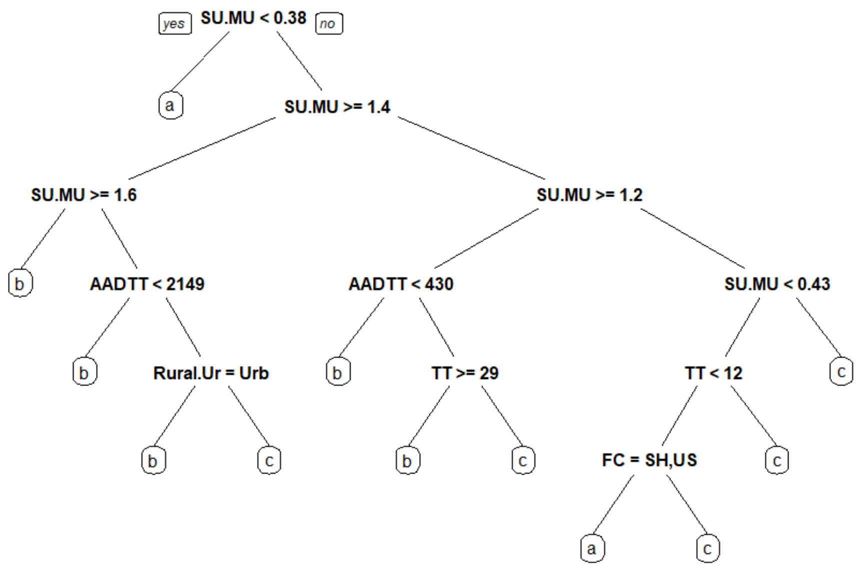


Figure 5.1 Decision tree to choose VCD cluster

In the above decision tree, SU.MU represents the ratio of single unit trucks to multiple unit trucks, TT. represents the percent of truck traffic, AADTT is the average annual truck traffic, FC is function class of the highway if it is interstate or US highway or state highway and Ru.Ur represents the rural or urban classification. a is the cluster 1 group, b represents the cluster group 2 and c is cluster-3.

For instance, if the design location has the SU/MU ration as 1.3 and having AADTT as 300 can probably have the vehicle class distribution similar to cluster-2.

5.3.2 Decision Tree for Single Axle Loading

Table 5.4 Summary of decision tree for monthly single axle loading data

CP	nsplit	relerror	xerror	xstd
0.133	0	1.000	1.000	0.055
0.089	2	0.734	0.831	0.051
0.046	3	0.645	0.706	0.048
0.032	5	0.552	0.617	0.046
0.030	7	0.488	0.565	0.044
0.014	9	0.427	0.528	0.043
0.012	11	0.399	0.569	0.044
0.010	12	0.387	0.556	0.044
0.010	14	0.367	0.556	0.044

Table 5.5Rank of independent variables in determining cluster for monthly single axle loading data

Truck Traffic	SU/MU	FC	Rural/Urban
59	25	9	6

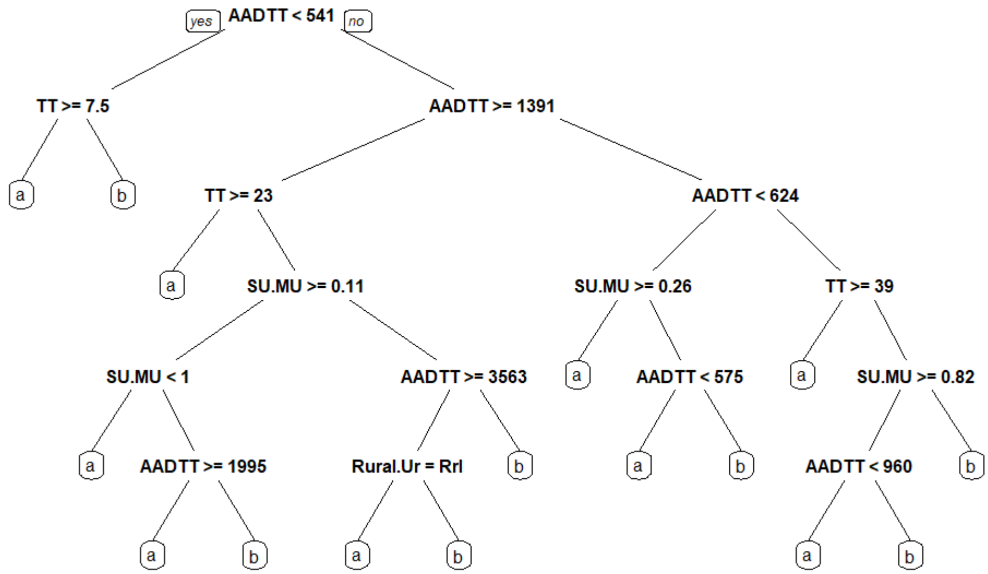


Figure 5.2 Decision tree to select single axle clusters

In the above single axle cluster decision tree, SU.MU represents the ratio of single unit trucks to multiple unit trucks, VALUETru is volume of truck traffic in particular month, a is the cluster 1 group, b represents the cluster group 2

For instance, if the design location has the SU/MU ration as 1.3 and having monthly truck traffic as 24000 can probably have the single axle loading similar to cluster-1

5.3.3 Decision Tree for Tandem Axle Loading

Table 5.6 Summary of a decision tree for monthly tandem axle loading data.

CP	nsplit	error	xerror	xstd
0.281	0	1.000	1.000	0.028
0.044	1	0.719	0.748	0.028
0.031	2	0.675	0.713	0.028
0.022	5	0.583	0.644	0.027
0.020	6	0.561	0.617	0.027

0.016	7	0.541	0.584	0.027
0.015	8	0.525	0.570	0.026

Table 5.7 Rank of independent variables in determining cluster for monthly tandem axle loading data

Truck Traffic	FC	Rural/Urban	SU/MU
53	20	15	13

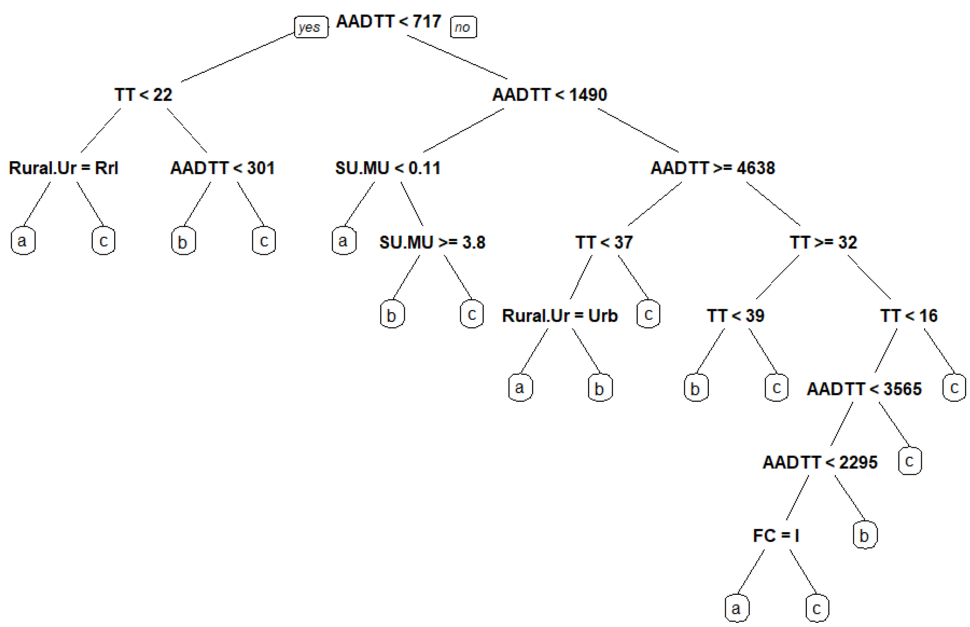


Figure 5.3 Decision tree to choose tandem axle loading cluster

In the tandem axle decision tree, SU.MU represents the ratio of single unit trucks to multiple unit trucks, TT. represents the percent of truck traffic, VAUETru is the volume of truck traffic in that month, FC is function class of the highway if it is interstate or US highway or state highway and R.U represents the rural or urban classification. a is the cluster 1 group, b represents the cluster group 2 and c is cluster-3.

For instance, if the design location is in rural interstate with low truck traffic can probably have the tandem axle loading similar to cluster-2

5.4 Multinomial Logit Regression Model

Traditional linear regression model requires the data to continue. However, one of the selected independent variables and the dependent variable are categorical, which implies linear regression cannot be a wise choice. Multinomial logit regression model can account for both continues and categorical variables. In R, the package 'nett' provides a function 'multinomial' that can develop a list of parameters based on independent variables, with which we can determine the dependent variable. Interpretation of results is explained below (Yves, C. 2012)

The output of the model has a summary block with coefficients and block with standard errors. Both the blocks have a coefficient and standard error for each independent variable for corresponding dependent variable category. A one-unit change in a variable may affect the probability of dependent variable to the corresponding fraction of the coefficient.

This regression model can be able to determine the ratio of the probability of selecting one cluster over the other for the five independent variables. For instance, monthly vehicle class distribution data has three clusters. Cluster-1 has taken base criteria and ran the multinomial logit regression model for the independent variables SU/MU, %TT, MADTT (continues data) and functional class (categorical variable). Results from the coefficient block can be interpreted as the equation given below.

$$Ln\left(\frac{P(Cluster\ 2)}{P(Cluster\ 1)}\right) = c_i + c_{\frac{SU}{MU}}\left(\frac{SU}{MU}\right) + c_{SH}(SH) + c_{US}(US) + c_{\%TT}(\%\ TT) + c_{MADTT}(MADTT)$$

$$Ln\left(\frac{P(Cluster\ 3)}{P(Cluster\ 1)}\right) = c_i + c_{\frac{SU}{MU}}\left(\frac{SU}{MU}\right) + c_{SH}(SH) + c_{US}(US) + c_{\%TT}(\%\ TT) + c_{MADTT}(MADTT)$$

Table 5.8 Coefficients block for VCD data

	Cluster-2	Cluster-3
(Intercept)	-19.635	-14.108
SU.MU	34.572	30.279
FCSH	1.066	0.459
FCUS	1.280	1.053
TT.	-0.006	0.056
MADTT	0.000	0.000

For instance, let us assume a site with nine times higher amount of single unit trucks than multiple unit trucks and classified as state highway with 10 percent truck traffic, 1900 monthly average truck traffic probability of cluster two over cluster 1 is higher (score=1.09E+127) than probability of cluster three over one(Score= 4.6E+112). This data is very similar to station AVC001 and we can observe this particular data set in cluster-2.

Table 5.9 Standard error block for VCD data

	Cluster-2	Cluster-3
(Intercept)	0.021	0.026
SU.MU	0.041	0.043
FCSH	0.037	0.041
FCUS	0.041	0.048
TT.	0.011	0.008
MADTT	0.000	0.000

Table 5.10 Coefficients and Standard error block for Single axle loading data

	Cluster-2	Std.Err
(Intercept)	-1.183	3.19E-12
SU.MU	-0.043	1.92E-12
FCSH	1.975	1.07E-13

FCUS	0.624	1.03E-12
%TT	-0.065	7.28E-11
MADTT	0.000	5.64E-07

Table 5.11 Coefficients block for tandem axle loading data

	Cluster-2	Cluster-3
(Intercept)	-1.672	-1.207
SU.MU	0.933	0.637
FCSH	-2.505	-2.765
FCUS	-1.623	-1.258
%TT	0.123	0.113
MADTT	-0.00000169	0.00000040

Table 5.12 Standard error block for tandem axle loading data

	Cluster-2	Cluster-3
(Intercept)	5.5E-12	5.4E-12
SU.MU	2.8E-12	2.1E-12
FCSH	1.8E-13	1.6E-13
FCUS	2.2E-12	2.8E-12
%TT	1.2E-10	1.0E-10
MADTT	8.4E-07	7.8E-07

CHAPTER-VI

6 CASE STUDY

6.1 Design Inputs

In chapter 5 three levels of traffic-inputs are derived to perform mechanistic pavement design. Based on the availability of data, knowledge on the traffic characteristics at design location and the funds available for the project the traffic input level is determined. To determine if there is significant change in the performance of the pavement while considering three different levels of traffic inputs, a case study is performed. In order to compare three levels, design location is to be selected in such a way that, site-specific data Level 1 inputs are available. Significant proportion of heavier truck traffic is observed on US-69 within Muskogee County, corresponding site-specific data can be obtained for the WIM station 021. So, this site is considered for the case study.

6.1.1 Pavement structure

Five layered new flexible pavement structure is considered at the design location. Top layer being asphalt concrete with 3-inch thickness, which is directly in contact with the vehicle tires. Second and third layer with 9-inch asphalt concrete together, which is slightly denser than the top layer. Fourth layer with graded aggregates (crushed stone) is serving as the base for the pavement structure. Fifth is unbounded subgrade layer assumed to exist to the greater depth to support the pavement. The performance measures are compared for the design life of 20 years.

Figure 6.1 Typical flexible pavement new structures used in the analysis

6.1.2 Traffic inputs

The performance of pavement structure is studied at one particular location for Leve-1, Level-2 and Level-3 traffic inputs to explain the variation among each input level. Significant proportion of heavier truck traffic is observed at WIM station 021, which is located on US-69 within Muskogee County. In order to evaluate the variation of performance predicted by ME-PDG software while using regional traffic clustering groups as inputs and statewide average traffic inputs, the following four different scenarios are compared.

- Scenario-1: Level-1 Site specific traffic inputs derived from WIM station 21
- Scenario-2: Level-2 Regional specific (Clustering group) traffic inputs based on decision tree model
- Scenario-3: Level-2 Regional specific (Clustering group) Cluster group traffic inputs based on Multinomial logit regression model
- Scenario-4: Leve-3 Statewide average traffic inputs

Scenario-1: Site-specific traffic data obtained from the station WIM021 (Level-1) is processed and traffic inputs that includes vehicle class distribution, monthly distribution factors and axle loading spectrum for single, tandem, tridem and quad axles are developed. For this traffic conditions performance of the pavement is predicted with the 90 percent confidence level.

Scenario-2: Decision tree (developed in chapter 5) is used to identify the traffic cluster groups based on independent variables at the design location. Traffic inputs are developed from the each cluster group, which includes vehicle class distribution cluster and axle loading spectrum cluster group for single, tandem, tridem and quad axles. Based on these traffic inputs performance of pavement structure is predicted.

Scenario-3: Regional specific Level-2 traffic input cluster group is identified by Multinomial Logit regression model (in chapter 5) based on independent variables at the design location. Traffic inputs for ME-PDG are developed from the cluster groups, which includes vehicle class distribution cluster and axle loading spectrum cluster group for single, tandem, tridem and quad axles.

Scenario-4: Statewide average Level-3 data is used to develop traffic inputs for ME-PDG. Irrespective of location or traffic patterns or independent variables, average of traffic data form every station with in Oklahoma is considered as input.

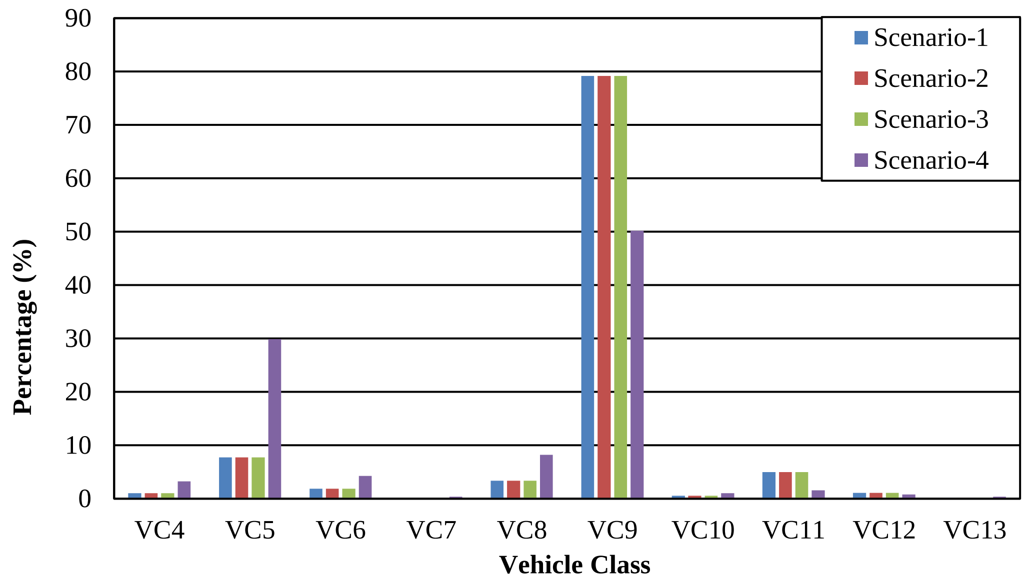
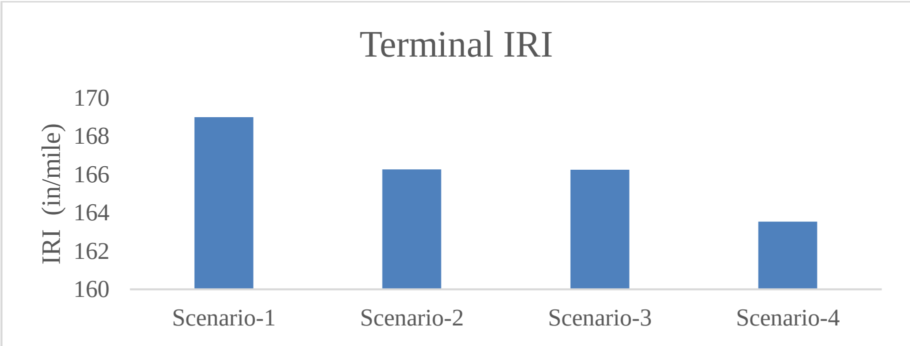


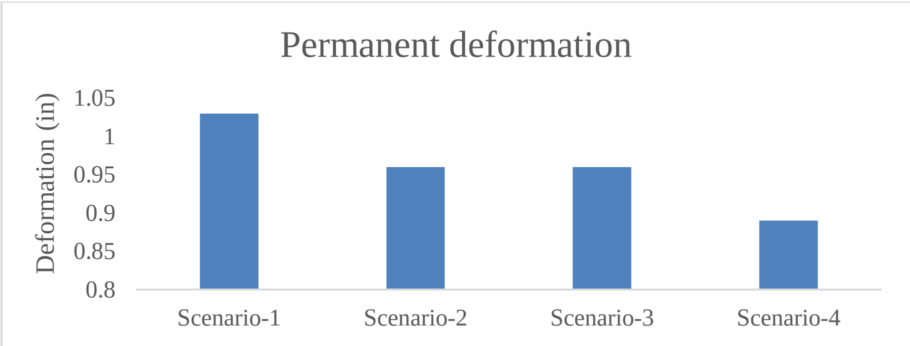
Figure 6.2 Vehicle class distribution for four scenarios

Vehicle class distribution in level 2 traffic input is very similar to the site specific level 1 traffic inputs. But in statewide average level 3 traffic inputs there is an influence of other stations in Oklahoma with predominant class 5 trucks, which results in lower proportion of class 9 trucks. This comparison is visualized in Figure.6.2.

6.2 Pavement Performance Comparisons

The performance of flexible pavement (described in 6.1.1) for 20 years design life is evaluated under four different traffic-loading conditions as mentioned in 6.1.2. The performance measures Design IRI value, permanent deformation in the AC layer and total pavement, fatigue cracking obtained from ME-PDG are summarized in Figure 6.3.





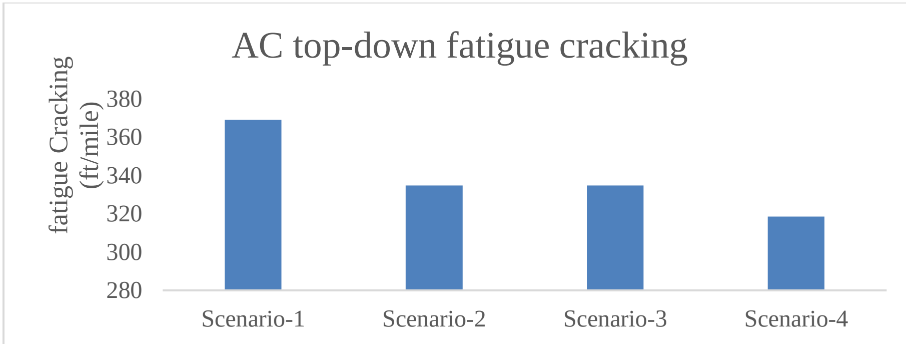


Figure 6.3 Performance comparisons for four scenarios

These results can provide evidence for the significant difference between Level 2 traffic inputs and Level 3 traffic inputs. According to mechanistic pavement design Level 2 provides more accurate performance measures when compared with level 3 inputs.

To quantify the variation in pavement design according to AASHTO 1993 guide for the three different traffic input levels, number of design ESALs are determined for each scenario. Figure6.4 explains design location has heavier traffic when compared with Oklahoma state average.

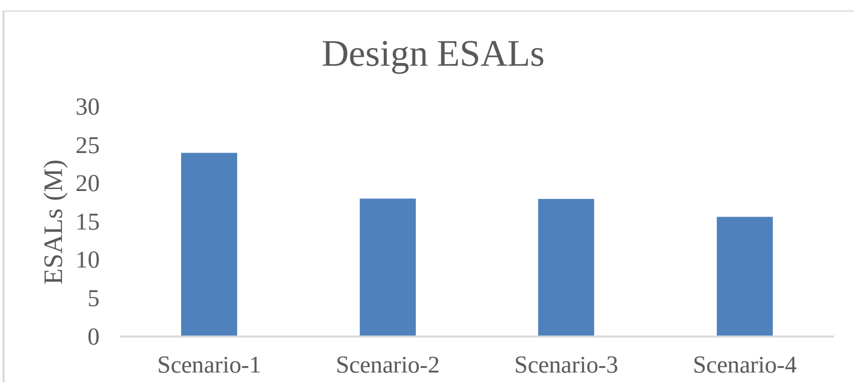


Figure 6.4 Design ESALs for four scenarios

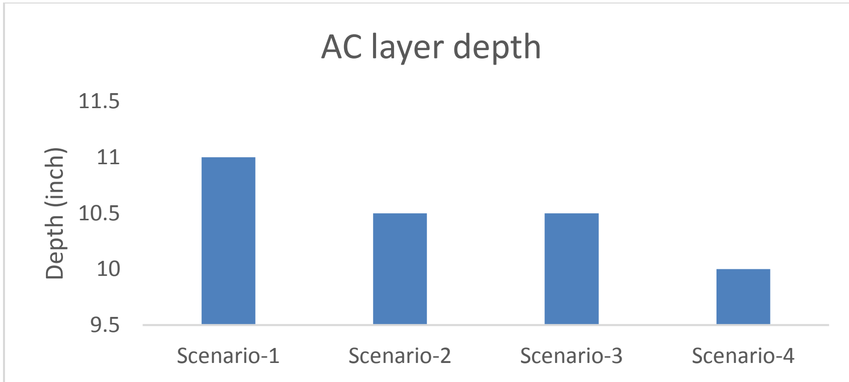


Figure 6.5 AC layer depth for four scenarios according to AASHTO 1993 design guide

Considering the design ESALs as the loading on the similar material properties, base and subgrade conditions mentioned in 6.1.1, required depth for asphalt concrete layer is determined and compared. The variation in the design AC layer depth is compared in Figure 6.5. In order to facilitate the design ESALs on the mentioned flexible pavement structure for 20 years of design life, Asphalt pavement structure requires 11inch depth of AC layer, for scenario 2 and 3 it requires 10.5 inch and for scenario 4 it requires only 10inch of AC layer.

7 CONCLUSIONS

The Mechanistic-Empirical Pavement Design Guide (MEPDG), later named as DARWin-ME and Pavement ME Design, proposes a more rational approach to characterizing traffic loading spectrum and material properties. The objective of this research is to develop WIM QC metrics for WIM data quality. Upon performing intensive study on the literature, methodologies available to generate site-specific (Level 1), region-specific (Level 2), and statewide average (Level 3) traffic inputs that are required for the Pavement ME Design are discussed. After performing the automatic data check followed by manual check, reliable data is selected for the analysis. By performing K mean cluster analysis on the selected data at both station level data and month level data, multiple clusters are developed for each Level 2 traffic input. The properties of each cluster group are discussed in brief. In addition, geographical spread of the clusters are visualized into maps. Later, based on availability independent variables are identified and tested for the correlation among themselves and selected accordingly. Decision trees, which can explain the process of selecting clusters based on each independent variable and multinomial regression model, which can explain the probability of being one cluster over the other are developed by training with the existing site-specific data. These models can assist the ODOT design engineers in selecting clusters for regional specific level 2 traffic inputs. The comparison among site-specific, regional specific values are discussed and presented along with the case study.

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APPENDIX A STATEWIDE TRAFFIC DATA QUALITY CHECK

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
2008															
1	N	3	P												
		4	D												
	S	1	D					d							
		2	P	a,b,d											
2	N	3	P												
		4	D					b							
	S	1	D			b						e	e	e	
		2	P												
3	E	3	P		a,b		a,b,d	a,b		b,d		b,d	b,d	b,d	b,d
		4	D												
	W	1	D	a,b	a,b	a,b	a,b	a,b							
		2	P						b,e	b		b,e	b,e		b,e
5	N	3	P												
		4	D				a,b	a,b	a,b	a,b	a,b				
	S	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P		a,b	a,b	a,b	a,b			a,b				
6	E	3	P												
		4	D						a,b	a,b					
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b
		2	P		a,b,d	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
7	E	3	P												
		4	D												
	W	1	D												
		2	P												
9	E	3	P												
		4	D	d			a,d	d	d	a,b,d	a,b,d	b,d	a,b,d	b,d	b,d
	W	1	D												

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
		2	P	b,d	b,d	b,d	b,d						d	d	b,d
10	N	3	P	a,b	a,b	a,b									a,b
		4	D				a,b	a,b	a,b						
	S	1	D				a,b	a,b	a,b	a,b	a,b	a,b			
		2	P	a,b	a,b	a,b	a,b	a,b							
11	N	3	P												
		4	D												
	S	1	D							a,b					
		2	P	a,b,d	a,d	b,d	b,d	a,d							
16	E	3	P	b,d	a,b,d										
		4	D												
	W	1	D												
		2	P												
21		2	D												
	S	1	D												
22	E	2	D												
	W	1	D												
23	E	2	D												
	W	1	D												
27	N	3	P							a,b					
		4	D	a,b,d	a,b,d	a,b,d		a,b							
	S	1	D												
		2	P	a,b,d	a,b,d										
28	E	3	P	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d
		4	D	a,b,d	a,b,d	a,b,d	a,b,d	a,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,d	a,d
	W	1	D			a,b	a,b			a,b	a,b	a,b	a,b	a,b	a,b
		2	P												
29	E	3	P												
		4	D												
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P		a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
30	N	3	P												
		4	D												
	S	1	D							a,b	a,b,d	a,b,d	a,b	a,b,d	a,b
		2	P						b.d	b.d	b.d	b.d	b.d	b.d	b.d
104	N	3	P	b.d	d	b.d								d	b,d
		4	D						a,b						
	S	1	D											a,b	
		2	P	b.d	b.d									d	b.d
114	E	3	P												
		4	D												
	W	1	D												
		2	P												
118	E	3	P	b.d	b.d	b.d									
		4	D	b.d	b.d	d									
	W	1	D												
		2	P	b.d											
2009															
1	N	3	P												
		4	D												
	S	1	D												
		2	P												
2	N	3	P							f	f	f			a,b
		4	D						a,b,d	f	f	f	a,b,d	a,b	
	S	1	D		a,b	a,b	a,b	a,b	a,b,d	a,b	f	f			
		2	P							f	f	f			
3	E	3	P			b,d	b,d				b,d	b,d	b,d	b,d	b,d
		4	D												
	W	1	D												
		2	P	b,d			b,d		b,d						
5	N	3	P							f	f	f		a,b	
		4	D					a,b	f	f	f	f	a,b	a,b	

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	S	1	D		a,b	a,b	a,b		a,b	a,b	a,b	a,b			
		2	P					a,b						a,b	
6	E	3	P								a,b				
		4	D				a,b	a,b	a,b	a,b	a,b				
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b			
		2	P	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b			
7	E	3	P	a,b	a,b,d	a,b	a,d	a,d	a,b		a,b	f	f	f	f
		4	D	d								f	f	f	f
	W	1	D									f	f	f	f
		2	P									f	f	f	f
9	E	3	P	b,d	b,d	b,d	b	b,d	d	d	d				
		4	D	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d
	W	1	D	d											
		2	P	d	d	b,d									d
10	N	3	P												
		4	D												
	S	1	D					a,b	a,b	a,b	a,b	a,b			
		2	P												
16	E	3	P												
		4	D												
	W	1	D												
		2	P												
21	N	3	P									d			
		4	D		a,b,c,d						f	f	f	f	
	S	2	D		a,b,c,d										
		1	P											a,b	b,d
22	E	2	D				a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	d
	W	1	D				a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	d
23	E	2	D											b,d	b,d
	W	1	D												
27	N	3	P												a,d

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
		4	D												
	S	1	D												a,b
		2	P	d									a,b		a,b,d
28	E	3	P	a,d	a,b,d	a,b,d	f	f	f	f	f	f	f	f	f
		4	D	a,d	a,d	a,d	f	f	f	f	f	f	f	f	f
	W	1	D	a,b,d	a,b	a,b	f	f	f	f	f	f	f	f	f
		2	P						a,b	f	f	f	f	f	f
29	E	3	P												
		4	D												
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P			a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b		
30	N	3	P		b,d,e	a,b,d,e	a,b,e	a,b,e	a,b,e	a,b,e	a,b,d,e	a,b,d,e	a,b,e	a,b,e	
		4	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b		
	S	1	D	a,b	a,b,d	a,b,d	a,b,d	a,b,d	a,b	a,b	a,b	a,b,d		a,b	
		2	P	a,b	a,b,d	a,b,d	b,d	b.d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b	
104	N	3	P	b,d		d			b,d						b,d
		4	D												
	S	1	D						a,b					a,b	
		2	P	b,d	b,d	b,d			a,d						b,d
114	E	3	P	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		4	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
118	E	3	P	e											e
		4	D												
	W	1	D												
		2	P												
2010															
1	N	3	P												a,b
		4	D											b,d	
	S	1	D												

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
		2	P		a,b					a,b				a,d	a,b
2	N	3	P	a,b	a,b		a,b	a,b					f	a,b,c	b,c
		4	D			a,b	a,b	a,b	a,b		a,b	a,b	f	a,b,c	a,b
	S	1	D						a,b				f	a,b,c,d	a,b,d
		2	P	a,b			a,b	a,b	a,b		a,b	a,b	f	a,b,c,d	a,d
3	E	3	P	e	e	e		e	a,b	a,b	a,b	a,b		b,c,e	b,c,e
		4	D				b,d						b,c	a,b,c,d	a,b,c,d
	W	1	D					b,d		b,d					
		2	P			b,d		b,d			b,d	b,d	b,c,d	a,c,d	b,c,d
5	N	3	P	a,b	a,b	a,b				a,b		a,b			
		4	D					a,b	a,b	a,b	a,b	a,b			
	S	1	D				a,b	a,b	a,b	a,b	a,b		a,b	a,b	
		2	P			a,b	a,b	a,b	a,b		a,b				
6	E	3	P							a,b		a,d	b,d	a,b,c,d	b,d
		4	D					a,b	a,b	a,b			d	a,b,c,d	f
	W	1	D				a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b,d	a,b,d
		2	P			a,b	a,b	a,b	a,b	a,b	a,b			a,b,d	a,b,d
7	E	3	P	f	f	f	f	f	f						
		4	D	b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,d		d	a,b,d	a,b,d	b,d	a,b,d
	W	1	D	a,b,d	a,d	a,d	b,d								
		2	P	e	e	e	e	e	e						e
9	E	3	P	e	e	e	e		e	e	e	e	e		
		4	D	a,b,d											
	W	1	D										b,d		
		2	P	a,b,c											
10	N	3	P		a,b										
		4	D												
	S	1	D				a,b	a,b	a,b		a,b	a,b	a,b		
		2	P								a,b	a,b	a,b	a,b	
11	N	3	P					e			a,b	a,b		a,b	a,b
		4	D										a,b	a,b	

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	S	1	D					a,b						a,b	a,b
		2	P		e						e		e	e	e
16	E	3	P	a,b,c								a,b,d	a,b,d	a,b,d	a,b,d
		4	D							a,b			a,b,d		
	W	1	D									a,d	a,b,d	a,b,d	b,d
		2	P									b,d	b,d	b,d	b,d
21	N	3	P	b,d		b,d			b,d						
		4	D												
	S	2	D						a,b,d	b,d	b,d	b,d	b,d	b,d	b,d
		1	P		a,b	a,b		a,b	b,d	b,d					
22	E	2	D	d	d	d	a,bd	a,bd	a,bd						
	W	1	D	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d	a,b,d					
23	E	2	D											a,b,d	a,b,d
	W	1	D				b,d	b,d	b,d						
27	N	3	P	b,d	b,d						f	f	f	f	f
		4	D									f	f	f	f
	S	1	D										f	f	f
		2	P	b,d	b,d								f	f	f
29	E	3	P												
		4	D												
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b,d	a,b,d	a,b,d	a,b,d
		2	P				a,b	a,b	a,b						
30	N	3	P				a,b		a,b	a,b			a,b	a,b	a,b,c,d
		4	D				a,b,d	a,b,d	a,b			f	f	a,b,c,d	a,b,c,d
	S	1	D	a,b	a,b	a,b			a,b				a,b	a,b	a,b
		2	P			a,b	a,b	a,b	a			f	f	b,d	b,d
104	N	3	P	d	d			a,d	a,d	a,b					
		4	D						a,b	a,b	a,b				
	S	1	D	a,b				a,b		a,b	a,b	a,b			
		2	P	b,d	b,d			a,d	a,b,d	b,d		a,b			
114	E	3	P	a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b	a,b		a,b

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
		4	D	a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b	a,b	a,b	a,b
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b		a,b				
		2	P	a,b	a,b	a,b	a,b				a,b				
118	E	3	P	b,d											d
		4	D												
	W	1	D												
		2	P												
2011															
1	N	3	P		a,b,d	a,b,d	a,b,d	b,d	a,b,d	a,b,d	a,b,d	a,d	b,d	b,d	a,d
		4	D	d	b,d										b,d
	S	1	D				b,d	b,d		a,b	a,b				
		2	P	a,d	a,d		b,d		a,b						
2	N	3	P			a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
	S	1	D	f	f	f	f	f	f	f	f	f	f	f	f
3	E	3	P	b,c,d	b,c	b,c		a,b,e	a,b,e		a,b,e			b,c	b,c,d
		4	D	a,b,c,d	a,b,c,d	a,b,c,d	b,c,d	b,c,d							
	W	1	D												
		2	P	a,b,c,d	a,b,c,d				b,d	b,d	b,d			d	a,b,d
5	N	3	P												
		4	D												
	S	1	D		a,d										
		2	P		a,d				a,b		a,b				
6	E	3	P	b,d	b,d	b,d	b,d	b,d	a,b,d	a,d	a,b,d	a,b,d	a,b,d	b,d	a,b,d
		4	D	b,d	b,d	b,d	a,b,d	a,b,d	a,b,d	a,d	a,b,d	a,b,d	a,b,d	b,d	a,b,d
	W	1	D	a,b,d	a,b,d	a,b,d	a,b,d	a,b	a,b		a,b	a,b,d	a,b,d	a,d	a,d
		2	P	a,b	a,b,d									a,b	
7	E	3	P												
		4	D	e	e		e						b,c,d	a,d	b,d
	W	1	D	f	f	f	f	f	f	f	f	f	f	f	f
		2	P	f	f	f	f	f	f	f	f	f	f	f	f
9	E	3	P	e	e	e	e	e	e	e	e	e	e	e	e

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
		4	D												
	W	1	D												
		2	P												
10	N	3	P												
		4	D			a,b	a,b	a,b	a,b	a,b	a,b		a,b	a,b	
	S	1	D		a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P		a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
11	N	3	P	a,b,d	b,d										
		4	D	d	b,d										
	S	1	D	f	f	f	f	f	f	f	f	f	f	f	f
		2	P	f	f	f	f	f	f	f	f	f	f	f	f
16	E	3	P												
		4	D												
	W	1	D												
		2	P												
21	N	3	P												
		4	D												
	S	2	D												
		1	P	a,b	a,b	a,b	a,b	a,b					a,b		a,b
22	E	2	D		b,d								a,b		
	W	1	D	b,d	b,d										
23	E	2	D	b,d	b,d								c		
	W	1	D												
27	N	3	P	f	f		a,b		a,b	a,b	f	a,b			
		4	D	f	f		a,b	a,b	a,b	a,b	f				
	S	1	D	f	f	a,b	a,b			a,b	f			a,b	a,b
		2	P	f	f	a,b	a,b				f		a,b		a,b
29	E	3	P	a,b,d	a,d	a,d	a,d	a,d	a,b	a,b,d	a,b,d	a,d	a,d		a,b
		4	D								a,b	a,b	a,b		a,b
	W	1	D	f	f	f	f	f	f	f	f	f	f	f	f
		2	P	f	f	f	f	f	f	f	f	f	f	f	f

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
30	N	3	P												
		4	D												
	S	1	D												
		2	P												
32	N	3	P						f	f	f	f	f	f	f
		4	D						f	f	f	f	f	f	f
	S	1	D						f	f	f	f	f	f	f
		2	P						f	f	f	f	f	f	f
104	N	3	P							f	f	f	f	f	
		4	D							f	f	f	f	f	
	S	1	D							f	f	f	f	f	
		2	P							f	f	f	f	f	
114	E	3	P										f	f	f
		4	D										f	f	f
	W	1	D										f	f	f
		2	P										f	f	f
118	E	3	P	b,d	b,d										
		4	D										b,d		d
	W	1	D												
		2	P	f	f	f	f	f	f	f	f	f	f	f	f
2012															
1	N	3	P												
		4	D												
	S	1	D												
		2	P												
2	N	3	P												
	S	1	D												
3	E	3	P										f	f	
		4	D										f	f	
	W	1	D										f	f	
		2	P										f	f	

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
5	N	3	P				a,b	a,b							
		4	D											a,b	
	S	1	D												
		2	P		a,b										
6	E	3	P												
		4	D												
	W	1	D												
		2	P		a,b	a,b									
9	E	3	P	f	f	f	f	f			f				
		4	D									f	e	b,d	b,d
	W	1	D								b,d	f	b,d		b,d
		2	P								b,d	f			
10	N	3	P												
		4	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b					a,b
	S	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
11	N	3	P												
		4	D	b,d	b,d	b,d								b,d	b,d
	S	1	D												
		2	P			b,d				b,d					
16	E	3	P	b,d	b,d			d	d	b,d	f	f	f	f	f
		4	D	a,b,d					a,d	b,c	b,c			a,b	a,b,c
	W	1	D												
		2	P												
21	N	3	P												b,d
		4	D												
	S	2	D												
		1	P												
22	E	2	D									b,d			b,d
	W	1	D												
23	E	2	D												

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	W	1	D												
25	E	2	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
	W	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
27	N	3	P			e	e	e	e	e	e	e		e	e
		4	D				a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
	S	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b
		2	P	b,d					a,b		a,b			a,b	a,b
28	N	1	P	f	f	f	f								
		2	D	f	f	f	f								
		3	D	f	f	f	f								
	S	1	D	f	f	f	f								
		2	D	f	f	f	f								
		3	P	f	f	f	f								
29	E	3	P												
		4	D												
	W	1	D	a,b	a,b	a,b,d									
		2	P		a,b		a,b						a,b	a,b	a,b
30	N	3	P	f	f	f									
		4	D	f	f	f									
	S	1	D												a,b
		2	P												
32	N	3	P		a,d	b,d	b,d	d							
		4	D												
	S	1	D		a,b	a,b,d	a,b					a,b		a,b	
		2	P		a,b	a,b,d		a,b							a,b
104	N	3	P	b,c	b,c					b,c	b,c		a,b		
		4	D	a,b						a,b					
	S	1	D	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b	a,b		
		2	P												
114	E	3	P	f	a,b					a,b		a,b	a,b	a,b	
		4	D	f				a,b			a,b	a,b		a,b	

WIM ID	DIRECTION	LANE	LANE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
	W	1	D	f											
		2	P	f	a,b										
118	E	3	P												
		4	D												
	W	1	D												
		2	P			e	e	e		e	e	e	e	e	E

Results of the data check for WIM data

	Sampled
	Copied from Adjacent Month
	unaccepted and un modified
	Less Volume & Not modified
	QC failed
	Manually accepted

a	**Gross Weight criteria Peak 1**
b	**Gross Weight criteria Peak 2**
c	**Front Axle Criteria**
d	**Drive Axle Criteria**
e	**No sufficient Fully Loaded trucks**
f	**No Data**

VITA

Srinivas Prudhvi Minnekanti

Candidate for the Degree of

Master of Science

Thesis: TYPE FULL TITLE HERE IN ALL CAPS

Major Field: Civil and Environmental engineering

Biographical:

Education:

Completed the requirements for the Master of Science in your major at Oklahoma State University, Stillwater, Oklahoma in December 2017.

Completed the requirements for the Bachelor of Science in Civil engineering at V.N.R. VJIET, Hyderabad, India in 2016.

Experience:

Transportation planner at CDM Smith (Summer-2017)
Engineering Intern at SEW Constructions (Summer-2015)
Engineering Intern at L&T HMRP (Summer-2014)